THE INTERACTION BETWEEN LAND USE AND TRANSPORTATION IN THE ERA OF SHARED AUTONOMOUS VEHICLES: A SIMULATION MODEL

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Ph.D. in the
School of City & Regional Planning, College of Design

Georgia Institute of Technology
August 2017

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ACKNOWLEDGEMENTS

I am grateful to many who have helped me in my endeavors to complete this academic journey. First, I would love to thank my advisor, Dr. Subhrajit Guhathakurta, for his invaluable guidance and support to help me go through this incredible journey of academic and personal growth. I also appreciate Dr. Steven French's academic mentorship and support throughout my graduate study. Each of my dissertation committee members, Drs. Ram Pendyala, Richard Fujimoto, and Bistra Dilkina, have provided guidance on the direction of this dissertation as well as critical advice regarding simulation and modeling methodologies. My dissertation committee helps me to develop my ability as a researcher and a lifelong learner and prepares me to start a career in academia. I am also grateful to Jinqi Fang for his suggestions on the programming part of this dissertation, enabling me to progress when model implementation presents challenges.

I am thankful to all the faculties and academic advisors at School of City and Regional Planning, Civil Engineering, and Computational Science of Engineering. My dissertation builds upon the knowledge I gained from my master trainings in all these schools, particularly in Dr. Jiawen Yang's GIS and transportation classes, Dr. Patricia Mokhtarian's discrete choice modeling class, Dr. Jorge Laval's advanced transportation method class, Dr. Bistra Dilkina's sustainable computation class, Dr. Richard Fujimoto's simulation class, and Dr. Polo Chau's data analytics and visualization class. I am also thankful to Dracy Blackwell, Robert Simon, Katrina Patton, and Janet Peterson, who make mundane paper works surprisingly easy for me. I also appreciate the company of my peer students at Georgia Tech, especially Fangru Wang, Camille Barchers, Ben Kraft, and

Kevin Lanza. I thank you for your enjoyable company through the many peaks and valleys during this graduate journey.

Last, and most importantly, I would love to thank my mother, Ping Li, and father, Anming Zhang, for their constant loving supports. They never cease to bring smiles to my face. I could never achieve this without their dedications.

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LIST OF SYMBOLS AND ABBREVIATIONS

ABM	Agent Based Model
ARC	Atlanta Regional Commission
AV	Autonomous Vehicles
ALV	Autonomous Land Vehicle
BAU	Business As Usual
CAP	Central Atlanta Progress
CBD	Central Business District
CDC	Centers for Disease Control and Prevention
DARPA	Defense Advanced Research Projects Agency
DES	Discrete Event Simulation
FEL	Future Event List
GHG	Greenhouse Gas
IVTT	in-vehicle travel time
LQ	Location Quotient
MNL	Multinomial Logit Model
NHTSA	National Highway Traffic Safety Administration
OD	Origin-Destination
OVTT	out-of-vehicle travel time
SAV	Shared Autonomous Vehicles
TCU	Transportation Communication Utility
SD	System Dynamics
TAZ	Traffic Analysis Zone
V2V	Vehicle to Vehicle
V2I	Vehicle to Infrastructure
VMT	Vehicle Miles Travelled
LIDAR	the Light Detection and Ranging

SUMMARY

We are on the cusp of a new era in mobility given that the enabling technologies for autonomous vehicles (AVs) are almost ready for deployment and testing. This promising technology together with the sharing economy will enable a new travel mode – Shared Autonomous Vehicles (SAVs), a taxi service without drivers. Recent studies have explored the feasibility, affordability, environmental benefits, and parking demand of the system in hypothetical grid-base cities. Despite these rapidly proliferating studies, it remains unclear how this affordable and environmentally friendly travel mode will influence residential and commercial location choices and potentially transform urban form. This dissertation addresses these gaps in the literature by answering the following research questions:

- How much parking will we need and where will they be located when the SAV system is a popular mode of travel?
- How will the SAV system influence residential location choices?
- How will the SAV system alter the spatial agglomeration of firms in the region?

To address the research questions, the operation of SAVs in the Atlanta Metropolitan Area is simulated using the actual transportation network with calibrated link-level travel speeds, travel demand origin-destination matrix, and synthesized household profiles. This real-world data-driven SAV model is used to determine the spatial distribution of parking demand under different parking price scenarios, including free parking, entrance based parking and time-based parking options. The results suggest the

SAV system can reduce over 90% of parking demand for households who participate into the system and give up their private vehicles. An SAV has the potential to eliminate 20 parking spaces in the City of Atlanta. The study then integrates the SAV simulation model with residential location choice models to reveal the shifts in residential location preferences in the era of SAVs. The outcomes indicate the SAV system is not going to induce urban sprawl and can make compact development more appealing by providing more convenient service in compact zones. Finally, it examines firm location choice models by industry sector by incorporating the SAV simulation results as an input. The model results show SAV system will accelerate the deindustrialization process via changing labor accessibility and available commercial and industrial land in TAZs.

The results of this study can inform land development policies designed to curb urban sprawl in the era of SAVs. The findings can be used to draft parking policies that are more responsive to the new SAV technology. In addition, the study breaks new ground in the estimation of potential impacts of SAVs on future residential and commercial building location in a metropolitan region.

CHAPTER 1. INTRODUCTION

Autonomous vehicles, cars that drive themselves, are close to becoming a reality. Multiple companies, including Google, Audi, Nissan, Tesla, and BMW, have announced plans to have fully automated cars by 2020. Recently, the U.S. Department of Transportation unveiled new policy guidance that reflects the reality that widespread deployment of AVs is now feasible (DOT 02-16 Press Release). Some optimistic analyses suggest that full automation can be achieved in approximately two decades in the U.S. (ABI Research, 2013; Stanley, 2013). It has been widely recognized that the social and legal infrastructure for large-scale implementation of autonomous vehicles is lagging. Moreover, the technology, to date, remains expensive for the public. Yet, the deployment of small-scale, low-speed, automated mobility on demand systems will soon be tested in Europe (CityMobil2 Project, n.d.) and possibly by Google and Uber shortly (Conye, 2015; Markoff, 2014).

The vehicle automation technology once combined with the sharing economy enables a new travel mode – Shared Autonomous Vehicles (SAVs), a taxi service without drivers. Existing simulation studies show the SAVs can be expected to be more affordable (Burns et al., 2013) and environmentally friendly (Fagnant & Kockelman 2015) to operate than privately owned Autonomous Vehicles (AVs). This new travel option provides numerous advantages when compared to conventional taxi and mobile-based on-demand systems, such as Uber and Lyft. SAVs can provide more affordable and accessible mobility to the public and optimize operation process via centralized service strategies (Fagnant & Kockelman, 2015; Shen & Lopes, 2015). The latest car-sharing and ride-sharing data released by existing mobile-based on-demand systems have already demonstrated positive changes in the carpooling mode split in cities where the service is enabled by the mobile platform (Uber , 2016; Lyft, 2016). Shen and Lopes (2015)'s results suggest SAV systems have the potential to further reduce the average waiting time and improve ride-matching experiences when compared to current mobile-based ride-sharing technology. All the above studies illustrate an optimistic picture regarding the feasibility and potential market penetration of the SAV system.

This promising SAV system will unarguably lead to changes in the urban built environment, particularly the quantity and distribution of urban parking land use as well as the preference in residential and employment location choices. The history of urbanization shows the emergence of innovative transportation technology, such as streetcar, bicycle, and automobiles, is always accompanied by significant changes in land use patterns and urban size. Therefore, the introduction of SAVs in the future will inevitably result in different urban structures, which may fundamentally alter the travel pattern, energy consumption, and carbon footprint of cities. However, it remains unclear how will the new landscape look like in the future. Several studies reveal that SAV system can lead to vehicle ownership reduction and increase vehicle utilization rate (Fagnant & Kockelman, 2015; Zhang et al., 2015b). Therefore, it is reasonable to expect a remarkable reduction in parking demand in urban areas. In the era of SAV, parking spaces could also be detached from destinations. There will be no need to bundle parking spaces with destinations, since clients can get out of the car at their desired destinations without worrying about cruising for parking. This will lead to a spatial mismatch between parking lots and destinations. In fact, it is also envisioned that SAVs may prefer to park in areas where parking is free or inexpensive to minimize total parking costs. Both the reduction and relocation of parking lots hold great promise for more sustainable urban development aesthetically, environmentally and economically. However, little knowledge has been gained regarding how much parking in general can be eliminated and where will the remaining parking spaces be located in the city.

The other on-going debate in both land use and transportation planning fields is whether SAV can help encourage compact development or contribute to urban sprawl. One critical query is that where will the households prefer to be located after the introduction of SAVs. Some expect more compact development patterns given the reduction in parking spaces (Zhang et al., 2015a) While others envisioned a more sprawled pattern given the significant reduction in transportation costs, as commute time may no longer incur high costs when multi-tasking is enabled in vehicles. To date, a limited number of study has focused on addressing how different changes brought by SAVs combined may influence residential location choices. More scenarios analysis regarding residential location choices is of great significant to both planners and traffic engineers. For planners, it is critical to understand the demand of residential land in the SAV scenario to guide public investment and zoning ordinance to prevent leapfrog development in rural areas. Meanwhile, for transportation agencies, a better understanding towards this question can contribute to devising policy tools to manage travel demand and transportation infrastructure investments, as the current literature suggests people's travel behavior and travel time budget are influenced by not only attitude and preferences, but also built environment and location in the region.

In addition to residential location choices, SAV may also influence employment location choices by reshaping the accessibility of land, especially the accessibility to skilled labor, and the availability of developable land. The opinions regarding how SAVs will affect employment location choices are also two-folded. Some suggest SAV may inspire more economic activities in peripheral areas by providing improved labor accessibility. On the other hand, the technology may also contribute to more densely developed commercial zones by removing minimum parking requirements at the parcel level. The variations in employment location decisions will eventually alter the spatial distribution of opportunities to incubate new business and expand existing services, providing implications for new economic structure and competitiveness of the region. Therefore, there is pressing need to obtain a better understanding regarding variations in employment location choices in the era of SAVs. Again, to author's best knowledge, almost no study has been conducted toward this end.

This work will fill in these gaps by developing a simulation model using the real transportation network with calibrated link-level travel speeds, travel demand origin-destination matrix, and synthesized household profiles. This SAV simulation model is then integrated with existing parking inventory, residential location choice model, and firm location choice model to address the following research questions using data from the City of Atlanta, USA:

- How much parking will we need and where are they located after the introduction of the SAV system?
- How will an SAV system influence residential location choices?
- How will an SAV system alter the spatial agglomeration of firms in the region?

This dissertation first examines the temporal and spatial distributions of parking demand under various parking price policies, including 1) free scenario, 2) entrance-based parking price scenario, and 3) time-based parking price scenario using the SAV simulation model. The results show over 90% of parking demand can be eliminated under various parking price scenarios. The outputs also suggest that the reduction in parking is unevenly distributed in the city. In the time-based parking (expensive) scenario, more parking spaces are eliminated in areas where the land price is high, such as Downtown and Midtown areas. The outputs also highlight potential social equity problems due to the concentration of parking land in disadvantaged communities in the expensive parking scenario. Additionally, the system may also have larger environmental impacts in the expensive parking scenarios, where SAVs prefer to empty cruising rather than parking to reduce the overall operating costs of the system. Understanding the impacts of SAV on parking and the influence of different charging policies on the system behavior can provide insights regarding amendments to minimum parking requirement, management of parking demand and infrastructure, and controlling negative externality of the system in the era of SAVs. The results are also meaningful for companies operating the SAV system, as they shine lights on the design of parking, cruising, and allocation algorithms to optimize the operation of the system.

The second question is explored by combining the SAV simulation model with a disaggregated residential location and relocation choice model. The outputs reveal potential variations in the choice of home location in the SAV scenario by market segments, i.e., whether households will relocate to more urbanized areas or exurban or even rural areas. The results suggest all households are going to relocate further away from office location to harvest the reduction in commute transportation costs. This indicates the commute VMT may increase significantly in the era of SAV. The results also suggest the younger generation is moving slightly further into the suburban area for better education resources and appealing quality of single-family properties. However, the younger households are not moving to rural areas, where the waiting time costs for SAVs are quite high. On the other hand, the senior generation is relocating towards the downtown area to avoid the high waiting time costs in their current home location. Therefore, SAVs will not induce urban sprawl into the rural areas, where the upfront waiting time cost is considerably higher. Based on the results, planning agencies can devise growth management tools, including limited development and open space designs in rural areas, down or up zoning, that can help maintain a sustainable urbanization process in the region. The results can also inform transportation departments to assess future challenges in commute VMT generation and alleviate congestions during peak hours via travel demand management, such as increasing the allowed vehicle occupancy from two to three in HOV lanes, subsidies to the use of local and regional transit systems.

The third question is addressed by integrating the SAV simulation model with an aggregated firm location and relocation choice model. The results show that SAVs may accelerate the deindustrialization process in major cities. The density of employment from the secondary sectors, including manufacturing, construction, wholesale, and TCU, in major cities decreases given the increases in development density in these areas. Meanwhile, the employment density for tertiary sectors, such as services, FIRE, and public, increases in first-tier cities in the region. The results also suggest that the total employment in various cities does not change significantly in the SAV scenario, indicating that firms still agglomerate in cities given the benefits brought by the scale of economy. The potential changing patterns can be of interests to both firms as well as transportation and planning agencies. The location choices incur high capital and time costs to firms and are critical to the success of businesses. A more comprehensive understanding of future economic structure in the region, therefore, can help firm leaders make more informed location decisions. From the transportation agency's perspective, the landscape of future employment across industry sectors can be critical in the design of freight and commute travel model and the prioritization of various infrastructure investments in the region. For planning agencies, the results can be used to forecast demand, intensity and composition of various commercial and industrial land uses, propose economic development strategies, and prevent or relieve potential social injustice problems in the SAV scenario.

The remainder of this dissertation is organized as follows. The second chapter provides background information regarding AVs and SAVs. The chapter also reviews and summarizes the existing studies regarding SAVs to show that limited studies have focused on the interaction of SAV system with urban land use. The third chapter summarizes the model methodology for the development of Discrete Event Simulation (DES) based SAV model and Multinomial Logit (MNL) Model based location and relocation choice models for households and firms by market segments. The fourth chapter implements the SAV simulation model in the City of Atlanta to determine the impact of SAV on urban parking land use. Chapter 5 applies residential location choice model, which was updated with transportation cost from the SAV simulation model applied in the 10-county Atlanta metropolitan area to examine potential changes in residential location choices in the era of SAVs. Chapter 6 presents the implementation of firm location choice model, which was updated using variables, including human capital access and developable land, obtained from the SAV simulation model, to determine spatial agglomeration patterns in the SAV scenario. Chapter 7 concludes all the findings, policy implications, model limitations and directions for future research.

CHAPTER 2. VEHICLE AUTOMATION AND URBAN FORM

This section reviews the concept of autonomous vehicles (AVs), shared autonomous vehicles (SAVs), and the ongoing debate regarding how vehicle automation can fundamentally change urban land use patterns. The section also summarizes existing theories and empirical studies to develop the nexus between land use and transportation that form the conceptual map for the research questions studied in this thesis.

2.1 Vehicle Automation Yesterday and Today

The idea of cars that drive themselves is not something invented recently but can be traced back much further. Early science fiction writings, such as Wonder Stories by David Keller, portrayed this technology to benefit human beings in various aspects. General Motors presented a conceptual model of radio-controlled autonomous vehicles in 1939 during the New York World's Fair to demonstrate the future of an automated highway. During the 1960s and 1980s, there were multiple attempts to create vehicle automation in the U.S., Japan, and Europe. However, these preliminary developments relied heavily on auxiliary infrastructures, such as metal guides and radio sensors that lead vehicles along the correct routes. The required infrastructure for these early prototypes meant that real-world traffic conditions could not be accommodated.

Autonomous technology started to attract public research funding in the late 1980s: the US Department of Defense funded the Defense Advanced Research Projects Agency (DARPA) Autonomous Land Vehicle (ALV) project; The European Commission funded the $800 million EUREKA Prometheus Project on autonomous vehicles. DARPA launched an annual "Grand Challenge" competition in 2004 to sponsor designs for autonomous vehicles. Stanford University's vehicle was the only one able to complete the challenge, and the designers were awarded $2 million. By 2007, 6 out of 11 participating vehicles were able to finish navigating the complicated competition route, including both the terrain area and the simulated urban environment (DARPA, n.d.). The public became aware of this technology in 2009 when Google, one of the pioneers in this field, initiated its self-driving car project (Google, n.d.).

To date, many commercial companies have dedicated numerous resources in AV research and development processes, and the technology is almost ready for application. Google claims that their AVs have traveled over 1.4 million miles in mixed traffic and through difficult terrain conditions in Mountain View, CA, Austin, TX and Kirkland, WA (Google Monthly Report, 2016). Vehicle manufacturers are also enthusiastic about self-driving technologies. Audi (Johnson, 2013), Nissan (White, 2013), Tesla (Kessler, 2015) and BMW (Elmer, 2013) have all announced plans to deploy fully automated cars by 2020. While the associated technologies to enable AVs are maturing quickly, many studies acknowledge that the social and legal infrastructure for implementing such systems is lagging. Yet, the deployment of small-scale, low-speed shared autonomous vehicles will be tested in Europe (CityMobil2 Project, n.d.) and possibly by Google and Uber shortly (Coyne, 2015; Markoff, 2014). A summary of AV technology development is illustrated in Figure 1.

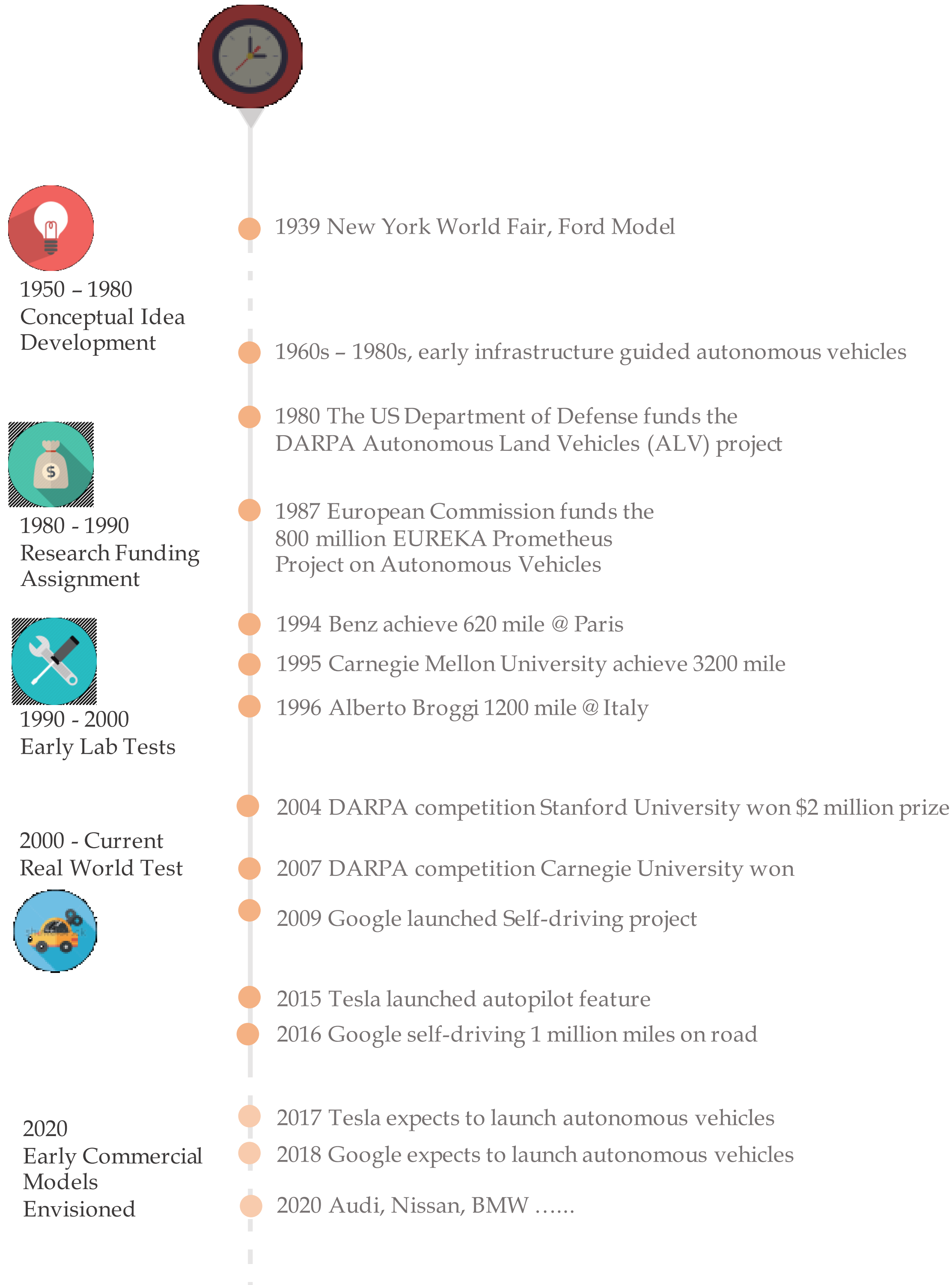


Figure 1: History of Autonomous Vehicle Development (Data Source: Stanley, 2013; Reorganized by Author)

There are five levels of automation defined by the industry (NHTSA 2013):

- Level 0 – No automation: The driver is in complete control of the vehicle. Warning and monitoring technology may be introduced for this type of vehicle.
- Level 1 – Functional-specific automation: the car only needs to be equipped with one automation technique, such as automatic parking.
- Level 2 – Combined-function automation: the vehicle should have with at least two automation features, such as lane position assistance, speed control, and congested environment navigation.
- Level 3 –Limited self-driving automation: Drivers are not required to constantly be in control of the system, but do need to maintain full vigilance and always be prepared to take over control as needed.
- Level 4 – Full self-driving automation: no human controlled will be required during travel.

Vehicles with automation levels 1-3 already exist. Many automakers have already offered some forms of "adaptive cruise control (Level 1 function)" which help the vehicle to keep a safe distance from the car ahead and brake if necessary to avoid collisions. Some companies have also introduced Level 2 functions into their products. For instance, Toyota and Ford can parallel park themselves with minimal driver assistance and Mercedes-Benz has "lane assist," which alerts the human driver when (s)he is drifting (Business Insider 2011). Tesla's Model S autopilot feature, which can be considered a Level 3 function, which occasionally requires hands on the steering wheel. The human interventions function as "training movements" to make the software more "intelligent" (Chang, 2015). All these vehicles cannot navigate properly without human drivers and are not considered as AVs in this study. The AVs studied in this dissertation are vehicles with Level 4 functions that can transport people from one point to another without human interventions.

Although the level 4 vehicle automation technology is still under development, the market penetration forecast of this new technology is promising. IHS Automotive (2014) predicts that AVs will be available to consumers by 2025, which is only five years after vehicle manufactures launch their prototypes of AVs. By the year of 2035, the sale of AVs is anticipated to rise to $11.9 million in the U.S. At that time, 54 million AVs are expected to be sold and used worldwide. By the year 2050, all the fleet on the road will be fully automated. Some more optimistic analysis suggests that fully automation can be achieved in approximately two decades in U.S. (ABI Research, 2013; Stanley, 2013). Similar adoption rates are applied to the U.K. market recently by KPMG (2015).

2.2 Benefits and Adoption Barriers of Autonomous Vehicles

2.2.1 Benefits of Autonomous Vehicles

AVs are envisioned to bring multiple benefits to the society, including improving travel safety, relieving congestions, improving mobility for the challenged population, curbing urban parking demand, and decreasing insurance costs.

2.2.1.1 <u>Safety</u>

In 2015, there were 38,300 fatalities caused by car crashes, according to National Safety Council. Additionally, approximately 4.4 million were injured in traffic accidents (NSC, 2015). The economic costs associated with these crashes were estimated at 152 million in the United States for the year 2015. According to NHTSA (2015), a majority of the traffic incidents (approximately 94%) were attributed to human error, including recognition errors (44%), decision errors (33%), and performance errors (21%), which can be significantly reduced or even eliminated by autonomous technology. One study estimates that in a world of 90 percent penetration of AVs the annual crash counts can be reduced by 4,220,000, saving 21,700 lives (Fagnant & Kockelman, 2015a).

2.2.1.2 Mobility

AVs could also improve the mobility of people who are physically challenged to drive, especially the senior population, children, and disabled population. In 2015 approximately 22 percent of the U.S. population is disabled, and about 13% is mobility challenged (CDC, 2015). People who are mobility challenged rely heavily on the transit system. The existing bus, rail, and paratransit system sometimes, however, fail to fulfill all these travel needs, which can lead to constrained activity outside homes and cause adverse psychological effects in the auto-centric American cities.

2.2.1.3 Economic Benefits

AVs can contribute to several financial savings in the future. The vehicles are envisioned to be more energy efficient, given the design of driving algorithms. Many technique reports estimate that the technology can cut fuel consumption by 15-20%. The insurance fee is expected to be lower as there will be fewer incidents. Most of the insurance company already provides discounts to vehicles equipped with certain automation features, such as lane and brake control. Finally, parking costs are also expected to be reduced, as the parking lots will be relocated to remote areas, where the land value is lower than downtown areas. Fagnant and Kockleman (2015) suggest $28.7 billion of saving in annual parking costs or approximately $550 per adopted AV at a 90% market penetration level.

2.2.1.4 Travel Experience

The autonomous vehicles will significantly improve current driver's travel experiences, since drivers can be more productive, such as texting, reading, web browsing, etc., or simply be more relaxed during the journey. Additionally, the promising Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication technologies also significantly increase the road capacity by platooning, which can be translated into less congestion and travel time.

2.2.2 Barriers to Large-Scale Deployment

Despite AVs demonstration multiple benefits compared with conventional vehicles, there remain numerous challenges for future adoption. These barriers are discussed separately in the following sections.

2.2.2.1 Technology and Security Barriers

Although the progress in technology advancement has already been impressive, there remain gaps in the existing algorithms to fully automated vehicles, especially given the complexity of the driving task. While computers are magnificent at conducting a large amount of simple mathematical tasks in a comparatively short period, they have struggled in accomplishing tasks that involve inferential thinking and prediction (Campbell, Egerstedt, How, & Murray, 2010). For instance, the computers may not be able to associate a child with a ball that bounces into the road (Silberg et al., 2012). Another technology barrier that AV industry faces is the lack of standardized protocols for V2V and V2I communications. Currently, different companies are competing intensively in autonomous vehicle development, and most are not sharing their R&D results with each other, which may lead miscommunication among vehicles from various companies. Finally, there remains concern regarding the security issues of AV technology. Fagnant and Kockelman (2015) suggest that computer hackers and terrorist organizations may target the AVs to trigger collisions and traffic disruption. The V2V and V2I technologies may be extremely vulnerable to such attack without a proper design of protocols. Nevertheless, it is unclear whether the current AV technology is designed securely enough to prevent these tragedies.

2.2.2.2 Legal Barriers

There is a need for a more matured legal framework to adopt the autonomous vehicle technology. Only two States, including California and Nevada, have enabled legislation for AV certification. Three other states, including Florida, Michigan and Washington D.C., have allowed AV tests. Similar legislation remains pending in 11 other states (Weiner & Smith, 2015). The AV legislative guidance varies significantly between California and Nevada. California's six-page legislation is the most comprehensive, covering guidance regarding insurance bonding, the ability to quick switch to manual driving, fail-safe system requirement, data storage before a collision, etc. Meanwhile, Nevada's legislation contains only 23 lines of definition and guidance. California has issued permits for Google, Audi, and Mercedes-Benz for AV testing. Certification standards for AV sales can be expected by the end of 2015. Nevada has issued permits for Google, Continental, and Audi for road tests. As of September 2015, no state has explicitly authorized AV test and use for individuals. The discrepancy of such legislations among states may incur uncertainty risks for AV manufacturers (Fagnant & Kockelman, 2015).

Some privacy concerns are raised when developing AV legislation (Fagnant & Kockelman, 2013). The core question is how to protect individual's privacy, as AVs generate gigabytes of data per second. The more detailed questions including 1) Who should own the data? 2) What type of data should be stored? 3) Who may access the data? and 4) To what ends will the data be used? It is quite obvious that sharing of such data can bring tremendous benefits, including better understanding towards travel pattern, more innovative congestion fee designs, traffic signal optimization, etc. The traveler's privacy will then be sacrificed. Therefore, privacy protection should be included in legislation to balance such tradeoffs. Without such protection, individuals may not even be willing to enter an AV.

2.2.2.3 Cost Barriers

One of the critical barriers, perhaps the largest obstacle, to large-scale AV adoption is the high add-on costs of AVs (Fagnant & Kockelman, 2015a). Compared with traditional vehicles, more technology, such as sensors, communication, and guidance, are required, so that AVs can function properly in the complicated urban environment. In 2012, a typical AV was equipped with approximately $200,000 worth of additional technology to operate properly (The Economist, 2013). The most expensive equipment is the Light Detection and Ranging (LIDAR) sensor, the cost of which ranging from $30,000 to $85,000. The one currently used by Google is approximate $70,000 (Fagnant & Kockelman, 2013).

There are primarily two ways to make AVs more affordable. First, update the current LIDAR technology to reduce the cost. However, according to projections from various sources, as shown in Table 1, the added cost may vary significantly based on the different speed of technology advancement. Second, give up vehicle ownership and split corresponding costs among users.

Table 1: AV added costs forecasts

Sources	IHS (IHS, 2014)	KPMG (Silberg et al., 2012)	Dellenback (Fagnant & Kockelman, 2015a)
2020	$7,000-$10,000	-	$25,000
2030	$5,000	-	$10,000
2035	$3,000	$1,000-$1,500	-

2.2.2.4 Other Barriers

Finally, in addition to the above obstacles, the large-scale deployment of AVs can also be challenged by people's perceptions. Studies suggest that senior drivers are more skeptical towards the technology compared with young drivers (Power, 2013; Silberg et al., 2012). Drivers will need time to accommodate themselves to the technology. There are also several ethical concerns to the adoption of AVs. The first concern is the exclusion of old vehicles in the urban transportation system. Critical mass is required to for AV adoption to achieve the benefits of automation, including congestion and prices reduction. Therefore, it is possible for the government to mandates AV adoption, which may marginalize old vehicle drivers. Drivers will be excluded from certain routes to optimize the performance of AVs (just like excluding bikes and pedestrians on the existing highway network). Additionally, drivers in vehicles may be treated differently, especially in the case of an accident involving both AVs and human drivers.

In summary, large-scale deployment of AVs can be challenged by technology security issues, immature legal framework, high add-on costs, public perceived safety concerns, and ethical issues. However, most of the existing barriers can be eventually resolved with the advancement of technology, evolution of legal framework, and development of new business models.

2.3 Autonomous Vehicles in the Era of Sharing Economy

AVs, together with the sharing economy, will enable a more affordable travel mode – Shared Autonomous Vehicles (SAVs). The concept of SAV, also known as aTaxi, was first envisioned by Kornhauser (2013), a professor at Princeton University. Initially, it is close to the existing concept of car-sharing programs, like Zipcar and Car2Go, but with a door-to-door service. This service was later associated with dynamic ride-sharing service by Fagnant and Kockelman (2014) and was simulated under Austin, TX context. A study of shared use of AVs suggests that the AVs can operate at approximately half of the per mile cost of existing privately owned vehicles (Burns, Jordan, & Scarborough, 2013). The electricity powered SAV system can still make profits at a fare rate of $0.13 per mile, which is even more affordable than the existing bus services (Bridges, 2015). More recently, Uber has also announced that it is going to cooperate with Carnegie Mellon University and design its prototype of AVs to be used in its mobile-app based car-sharing and ride-sharing (Uberpool) service (Coyne, 2015). Therefore, Uber is on the verge of implementing the Shared Autonomous Vehicle (SAV) system.

Although the SAV system shares many characteristics with the existing car-sharing, ride-sharing, and taxi system, it is significantly different from (and outperforms) each of these systems, as elaborated in the following sections.

2.3.1 SAV and Car-sharing System

The car-sharing program offers self-serve access to vehicles located at fixed stations on the transportation network. Users are usually obligated to return the vehicles to the original rental stations or at least other stations in the network, which dramatically reduced the flexibility of trips for users. SAV, on the other hand, can offer more convenient, point-to-point, service for users, rendering this new travel mode far more appealing than the existing car-sharing programs, like Zipcar, Car2go, and City Carshare. The two systems, however, do share a common operation issue – the imbalance of vehicle supply and client demand across the service area. The SAV system, unlike the existing car-sharing programs, can solve such problem more effectively and cheaply. The SAV system can arrange the vehicles to relocate themselves based on anticipated travel demand and the real-time distribution of vehicles in the system.

2.3.2 SAV and Dynamic Ride-sharing System

The existing literature usually divides the concept of ride-sharing into static ride-sharing and dynamic ride-sharing. Static ride-sharing is also known as carpool or vanpool, where people who know each other group together to travel, typically for reoccurring trips, such as commute. Meanwhile dynamic ride-sharing, also known as ad-hoc ride-sharing or instant ride-sharing, usually refers to matching trips among strangers for nonrecurring trip purposes. In short, static ride-sharing is arranged based on already known trip information, while dynamic ride-sharing is managed based on incoming flows of requests without preset travel plans.

While static ride-sharing represents a small portion of vehicle trips, the dynamic ride-sharing enabled by mobile-based applications is on the rise. Data from Census Bureau suggest that ride-sharing mode split decreased from approximately 20% in the 1970s to 10% in 2008. The mode split of static ride-sharing or carpooling mode split leveled off in the recent years (U.S. Census Bureau, 2012). However, the latest data released by Uber, Lyft and Sidecars suggest an increase in the share of dynamic ride-sharing mode, after they incorporated the “pool” service into their mobile applications. Uber activates its UberPool service in San Francisco, Paris, New York, Los Angeles, Austin and most recently, Atlanta. Their data indicate that thousands of users use such service more than five times per week for commuting purposes, and millions of trips have been pooled together. The trip match rate in a high-density neighborhood is over 90%. Lyft reveals that their LyftLine service makes up a majority of its rides in San Francisco. Sidecar's SharedRides account for approximately 40% of its overall rides. All these data draw a positive picture for the carpooling mode split in cities where the service is enabled by big and open data powered ride matching applications. Hence, in this study, dynamic ride-sharing service, similar to the ones offered by Lyft and Uber, is incorporated into the SAV system, except that there will be no drivers but only riders and automated vehicles in the system.

2.3.3 SAV and Taxi System

The SAV system is similar to a taxi system in many ways; however, the SAV system can be more appealing by operating under a central optimization system, resulting in less energy consumption, more efficient use of fleet capacity and better user experiences. The operation of the current taxi system is hardly optimized because complete information regarding the temporal and spatial distributions of demands and supplies is barely accessible to drivers and clients. Although the mobile-app based systems, such as Uber and Lyft, have real-time models to identify potential demands to feed the drivers and arranging empty vehicle supplies, the performance of the system may still be hampered as individual drivers may prefer to optimize their personal interests versus the system-wide benefits.

2.4 SAV and Urban Form

Numerous compelling studies suggest that advances in transportation technology lead to transforming and irreversible changes in urban structure and forms. The development of streetcars in the 1950s triggered the initial wave of suburbanization, which accelerated with the advent of the automobiles in the 20th century. Today, we are on the cusp of the new mobility era powered by automated vehicles. This disruptive technology is expected to reduce urban parking demand and fundamentally influence urban development patterns.

2.4.1 SAVs and Urban Parking Land Use

The proposed SAV system is expected to reduce vehicle ownership (Fagnant & Kockelman, 2014) and increase vehicle utilization rate (Fagnant & Kockelman, 2015b; Zhang, Guhathakurta, Fang, & Zhang, 2015b) and both can be translated into reduced parking demand in urban areas. Moreover, given the fact that passengers are expected to be dropped off directly at the destination before parking, there will be no need to open doors in the parking lot, which can further reduce the required parking space for automated cars (Hayes, 2011; The Economist, 2013). In addition to reducing parking spaces, the SAV system can also fundamentally rearrange the spatial distribution of parking lots. SAVs can detach parking lots from destinations, as SAVs will be able to relocate to park or keep serving incoming clients. The most recent SAV simulation effort with a focus on urban parking demand reveals that the system can significantly reduce the parking demand for households who participate in using the service and giving up their privately owned vehicles in a hypothetical grid based city (Zhang, Guhathakurta, Fang, & Zhang, 2015a). The study also suggests that the urban parking demand varies throughout the city: there will be more parking demand in the urban center area. Such results may change once the parking prices are included into the simulation model.

The reduction and relocation of parking spaces offer remarkable opportunities for more sustainable urban developments. Existing research has already shown that parking is problematic, economically, environmentally and aesthetically. Chester, Horvath, and Madanat (2010) developed multiple scenarios of parking inventory estimation in the United States. Even the moderate scenario leads to billions of parking spots, which is similar to the assessment proposed by Shoup (2005). The total area of these parking lots is approximately 6,500 square miles, which is even larger than Connecticut. Chester et al. (2010) also suggest that the costs of parking in the United States can range between $4 and $20 billion a year. Although parking is mostly free of charge, the fee for parking lot construction and maintenance are passed to the public (no matter whether they own a car or not) by developers in one way or another, such as an increase in the rent. Parking also contributes to adverse environmental impacts. Shoup (2005) estimates that approximately 30-minute cruising time is wasted in downtown areas by drivers searching for parking lots, resulting in tons of gallons of gas consumption and greenhouse gas (GHG) and air pollutants emissions throughout the year. Additionally, asphalt, widely used as the pavement material for parking lots, tends to trap heat. The trapped heat will exaggerate the urban heat island effect, which affects public health and increases building energy consumption in urban areas, especially during the summer time. The coming of SAV system, therefore, holds promise not only for alleviating parking-induced environmental problems but also for unlocking the tremendous social and economic values embedded in the land that is currently occupied by parking spaces.

In short, there is a need for more robust real-world data driven simulation models to generate new knowledge regarding how the spatial and temporal distributions of urban parking demand may change after the emergence of SAVs. The simulation results will help better prepare urban planners, designers, and decision makers to grasp this opportunity to guide the city towards more sustainable development.

2.4.2 SAVs and Residential Location Choice

There are ongoing discussions regarding whether vehicle automation will lead to more compact development or more sprawled urban landscape. On the one hand, driverless cars would promote densification because they will curb the need for parking. However, it is also possible that driverless cars would facilitate dispersion and sprawl by making travel less burdensome, if not more interesting, and potentially reduce travel time costs (*Economist* 2013; Hayes 2011; Fagnant and Kockleman 2014). The essential question regarding how SAVs may influence urban form is how the SAVs are going to affect people's preferences for residential location choices.

The existing literature suggests that transportation costs and accessibility play an essential role in residential location choice. Alonso (1964) applied the bid-rent concept from Von Thünen (1826)'s agricultural land use model to residential land uses and suggest residential location choice is made to optimize the transportation costs, land size, and goods expenditures. More recent empirical studies also indicate that transportation costs or travel time to various destinations are critical in the decision-making process for home location. Commuting time is always found to be negatively associated with the residential utility function (Guo & Bhat, 2007; Habib & Miller, 2009; Lee, Waddell, Wang, & Pendyala, 2010). Some other studies differentiate commuting time for private vehicles and public transit, and both variables turn out to be negative and significant (Pinjari, Bhat, & Hensher, 2009; Pinjari, Pendyala, Bhat, & Waddell, 2011). One study suggests that transit commuting time is considered as more critical than commuting time by private transportation (de Palma, Picard, & Waddell, 2007). The introduction of SAV system may have different impacts on travel time throughout the city because the uneven distribution of vehicles caused by travel demand pattern in the city. However, there virtually has been no rigorous study towards the spatial variation in the SAV availability by the time of the day and by different travel patterns. Moreover, no study has rigorously focused on how the uneven distribution of SAVs may influence residential location choices in the SAV dominant scenario.

2.4.3 SAVs and Employment Agglomeration

Theories regarding employment location choices can also be traced back to 19th century. Weber (1909) formulated the theory of industry location, dictating that firms locate in places that minimize the transportation costs of raw materials and final products.

The spatial theory of urban firm location choices is initiated by Losch's idealized hexagonal markets allocation of firms (Losch, 1954) and Christaller's work regarding central place and hierarchy of cities (Christaller, 1933). Both Losch and Christaller's work provide conceptual framework explaining the role of accessibility to input materials and output markets in firm location choices.

However, these theories do not explain the spatial agglomeration of firms. The co-locating phenomenon of firms is later explained in the theoretical works related to agglomeration economies. This line of theory suggests that the returns to scale are not constant, but rather increase for firms that cluster with other firms either within or outside of their industry sectors (Marshall, 2009). The localization economies indicate that firms tend to co-locate due to three benefits offered by agglomeration, including buy-suppler networks, labor market pooling, and knowledge spillovers. Meanwhile, there are also factors that may prevent the formulation of the extremely high density of firms. These factors are generally associated with negative externalities caused by agglomeration, such as congestions, pollutions, and high rent in urban centers. Recent empirical models, also include other amenities, such as government policies and taxes into consideration (Waddell & Ulfarsson, 2003).

Based on the existing spatial theories, accessibility to resources and amount of developable land play an essential role in firm location choices. The introduction of SAVs as a form of urban mobility service will clearly change firms' accessibility to human capitals as well as the availability of land in the region. Therefore, this envisioned travel mode would not only affect residential location choices but also employment location choices. First, SAVs will increase firms' accessibility to labors by reducing the transportation costs. Several studies suggest that the mobility service provided by SAV system will be more affordable compared with privately owned vehicles and even some public transit services. The mile based cost for SAV ranges from ¢13-50/mile according to recent articles and commercial assessment reports (Albright, Bell, Schneider, & Nyce, 2016; Barclays, 2016; Bridges, 2015; Burns et al., 2013). The SAV cost varies depending on the assumptions in technology development, future insurance rate, maintenance frequency, vehicle fuel type, as well as the density of travel demand. In the most optimistic estimation, where electric SAV system fulfills the travel demand, the system costs approximately ¢13/mile and can still anticipate 30% of marginal profits. Despite the wide range in SAV cost estimation, the cost of SAV is well below the current cost for an average sedan, which is estimated at ¢75/mile (AAA, 2016).

Beyond the mile based cost reduction, SAVs can further reduce transportation costs by enabling multi-tasking in vehicles. Given that the burden of driving is eliminated in self-driving cars, the in-vehicle travel time (IVTT) may be a nuisance to drivers, as the people can be productive or simply relax in the car. Therefore, it is anticipated that the primarily travel time costs in the era of SAVs will be the out-of-vehicle travel time (OVTT) costs, i.e., waiting time costs. In other words, the accessibility to destinations or resources is no longer an inversed function of distance, but rather negatively associated OVTT costs incurred at origins and destinations. The average waiting time costs may vary throughout the city, depending on the distribution of available SAVs. Although the SAVs can relocate to balance the distribution of service in the city, the OVTT costs in higher density districts are expected to be lower. This indicates that compactly developed zones be more accessible to various markets and resources in the region.

Moreover, SAVs may also change the spatial distribution of developable land by eliminating a significant amount of parking lots in urban areas. Simulation results from both hypothetical grid and real-world network based model settings all suggest that over 90% of the parking lots can be eliminated in the future (Zhang et al., 2015a; Zhang & Guhathakurta, 2017; International Transport Forum, 2015). Additionally, the reduction in parking land is unlikely to be uniformly distributed in the city. More reduction is anticipated in areas with high land values, given SAVs are programmed to park in zones that minimize total parking expenses (Zhang & Guhathakurta, 2017). This indicates that more land will be available for development in areas with comparatively higher land values, such as urban core and commercial sub-centers, where currently a considerable amount of land is zoned as parking spaces to meet the minimum parking requirements.

2.5 Current Research and Gaps

There have already been inspiring studies evaluating various impacts of the SAV system using the simulation approach. Ford (2012) reviews the present social and legal barriers to the SAV system adoption. The study also constructs a simple but intuitive model to evaluate the performance of a shared taxi system, *ataxi* system, with fixed service stations distributed every half-mile in the region to determine whether the system is sufficient to fulfill the existing travel demand. The results suggest that the system is entirely feasible, despite the fact that the current legal environment will pose several barriers.

Kornhauser (2013) evaluate the feasibility of a shared autonomous taxi system with a similar setting as Ford (2012) in various counties in New Jersey, and they find that SAVs can facilitate an increase in ride-sharing travel behavior. Burns et al. (2013) develop a more advanced agent-based simulation model to evaluate the economic feasibility of a ubiquitous SAV car-sharing system. The simulation results imply that the cost per trip mile can range from $0.32 to $0.39, depending on the fleet size of the SAV system. This travel cost is more affordable than owning and operating a private vehicle. Bridges (2015) suggests that this mile-based cost can even be further reduced to $0.13 if the SAVs are powered by electricity and the entire system can still anticipate a reasonable share of profit. In sum, all the above studies suggest that SAV system is economically feasible and potentially affordable for the public.

Fagnant and Kockelman (2014) investigate whether the SAV system is environmentally sustainable. Their model assumptions are similar to Burns et al.'s model, with some adjustment, e.g. introduction of different speeds during peak and off-peak hours and directional effect of traffic, to better explore the gas consumptions and emissions of the system. Their study results show that each SAV has the potential to replace approximately 11 privately owned vehicles. Furthermore, some environmental benefits such as reductions in energy consumptions, GHG emissions, and air pollutants emissions per vehicle life cycle can be expected once the SAV system starts to serve 5% of the population within a ten by ten-mile grid-based study area. However, Fagnant and Kockelman's study suggested that the SAV system comes with approximately 5% additional unoccupied VMT generated during client picking up the process. This side effect may be alleviated or even eliminated through the increase of ride-sharing behavior (Fagnant & Kockelman, 2014).

Several recent attempts have been made to explore the potential impact of SAV system on other aspects under the hypothetical grid-based urban modeling framework. By extending Fagnant and Kockelman's (2014) model, Chen, Kockelman, & Hanna (2016) analyzed the potential mode share and charging station distributions for the electrified SAV system within the context of the grid based region. One more recent grid-based hypothetical simulation study explored the impact of SAVs on urban parking demand and found that significant amount of reduction can be achieved for participated households (Zhang et al., 2015a).

Some exciting attempts have been made to examine the operation of SAV system within a real-world context. One study navigated the performance of the system in Austin, TX (Fagnant, Kockelman, & Bansal, 2015). Another study contributed to explore the impact of the system on urban traffic in the City of Lisbon, and the results suggest there will be a vast volume of traffic increase (International Transport Forum, 2015). Spieser et al. (2014) studied the feasibility of the SAV system and the level of service the system may offer if the system replaces all the fleets on the road in Singapore. Their results show that not only SAV system is capable of serving the entire population; the level of service is also quite impressive, surpassing the existing transit and privately owned vehicles. Rigole (2014) used the SAV system to serve all the commuting trips in Stockholm and identified the potential environmental benefits that the system may provide. Shen & Lopes (2015) replaced existing New York taxis with SAVs, and their simulation suggests that SAV system can reduce the average waiting time for clients via using advanced centralized dispatching algorithm.

Although the literature regarding the SAV system is growing rapidly, a limited number of studies have focused on how SAVs may influence urban land use. It is still unclear how much urban parking spaces are likely to be reduced and how will the spatial and temporal distributions of parking demand be changed once the SAV system is implemented. Little has been discussed regarding the whether the availability of the SAV service is uniformly distributed throughout the service area. If the SAV service is not evenly accessible throughout the entire city, how will people's residential location choice evolve over time? Finally, how will the SAV system change the spatial agglomeration patterns of firms by altering the accessibility of land and availability of developable land in the region? Just as *The Economist* (2013) warned recently: "Town planners, property developers and builders need to start thinking about the effect of self-driving technology on demand for roads, parking, housing and so on. So far there is little sign that this is happening." This dissertation begins to fill these gaps through a simulation model, which is developed to estimate the potential impact of the SAV system on urban parking land use, residential location choices, and employment spatial agglomeration patterns in the real-world context. Three specific research questions, listed as below, will be addressed.

- How much parking land use will we need and where will it need to be located after the introduction of SAV system?
- How will an SAV system influence residential location choices?
- How will an SAV system alter the spatial aggregation of firms in the region?

The simulation approach is used in this dissertation, as the SAV system is still under development and it is impossible to gather empirical data for further analysis. In fact, most of the existing literature utilize various simulation approaches to explore SAV scenarios by controlling different model parameters (or assumptions), such as market penetrations, business models, and mode splits. Models used to address the research questions are elaborated in Chapter 3.

CHAPTER 3. METHODOLOGY

This chapter presents the methodology details for SAV discrete simulation model, residential and employment location choice models, as well as the design of relocation choice model for households and firms correspondingly.

3.1 Discrete SAV Simulation Development

This section first reviews the prior SAV simulation model efforts, including model contents, structures, assumptions, simplifications and the use of time variables. Building upon these pioneering model efforts, Section 3.1.2 discusses the development of a discrete event based SAV simulation model. This model serves as the foundation to address the three research questions in this dissertation.

3.1.1 Prior SAV Simulation Model Review

SAV simulation models from both academic journals and industrial technical reports are collected to review conceptual models and embedded simulation-modeling paradigms. Most of the existing SAV studies construct models in hypothetical grid-based cities (Burns et al., 2013; Chen, 2015; Chen et al., 2016; Douglas, 2015; Fagnant & Kockelman, 2014, 2015b; Ford, 2012; Kornhauser, 2013; Zhang et al., 2015a). Some pioneering studies simulated the performance of the SAV in the real-world context (Fagnant et al., 2015; International Transport Forum, 2015; Rigole, 2014; Shen & Lopes, 2015; Spieser et al., 2014).

3.1.1.1 SAV Model Content and Structure Review

Most of the developed models share similar model contents, i.e. model inputs, model entities, simplifications and assumptions, and SAV system structures, with some extensions included to tailor the simulations given the study objectives, such as economic costs analysis, environment impact evaluation, charging station location selections.

Ford (2012) establishes an SAV model to estimate the demand for autonomous taxis or the feasibility of the SAV system in Mercer County, assuming the travelers can only get on and off at fixed taxi stands, which is similar to the settings of current car-sharing programs. The model simulates travel demand based on local travel survey and assigns origins and destinations to the closest half-mile grids. The model uniformly distributes the taxi stands in the transportation network at the beginning of the day, and eliminates the ones with limited service demands from the system during the simulation process. The model does not account for vehicle self-relocation process, as the quantity of service request at each taxi stand is the primarily simulation output to determine the feasibility of the system given existing travel pattern in the county. Based on similar settings, Kornhauser (2013) develops a model to estimate the ride-sharing potential for SAV system in New Jersey.

Burns et al. (2013) simulate the operation of SAV system in three grid-based cities. The system provides a door-to-door service with the resolution of half-mile grids. The model uniformly distributes trips within the hypothetical city that will be served by the closest available SAV throughout the day. The travel speed of the SAVs is constant throughout the day and across the entire network. When a vehicle completes a trip, it will head to the origin of the next assigned customer. If the vehicle is no longer assigned to any other client, it will park at the destination of the last client and wait for the next call. To obtain mile-based operation costs for SAV, the model also assumes the sale price for self-driving cars and other vehicle service costs, such as insurance, gas, and maintenance costs. The model updates every 5-minute virtual time.

Fagnant & Kockelman (2014) build upon Burn's model and improve the model by refining the demand generation model, including traffic congestions in travel speeds simulation, and adding the vehicle self-relocation component into the model. In this model, SAVs travel slower during peak hours, and self-relocate to balance supply and demand in the system. These extensions are critical to achieving their simulation objective, which is the environmental impact of SAV system, as the existing studies suggest energy consumption and emissions of vehicles is closely associated with vehicle speeds and traveled miles. Chen (2015) and Chen, Kockelman, & Hanna (2016) extend Fagnant and Kockelman's model by incorporating vehicle charging component into the simulation to explore the quantity and the spatial distribution of potential charging stations for electricity powered SAV system.

The above SAV simulation studies mimic the operation of SAV without ride-sharing services. Several hypothetical city based studies incorporates dynamic ride-sharing services, which is similar to the Uberpool and LyftLine business model, into the SAV system (Fagnant & Kockelman, 2015b; Zhang et al., 2015a). In these simulation models, the SAV system matches clients with close by origins, destinations (grid cells) and departure time to share rides. The SAV system matches two trips together if both clients are willing to share rides with strangers. Thus, these models include an additional trip-matching component into the design of SAV model. The results suggest that dynamic ride-sharing can contribute to reduced Vehicle Miles Travelled (VMT), less parking demand, and smaller SAV fleet size.

Although most of the efforts, to date, have been made towards simulating the operation of SAV system in hypothetical context, a few studies carry the work forward by exploring the system based on real world network and travel patterns. Fagnant et al. (2015) construct an SAV model with local transportation network and travel pattern from 24-mi by 12-mi region core of Austin, TX with a resolution at the Traffic Analysis Zone (TAZ) level, and five-minute model updating frequency. The link level travel speed is updated hourly. Another model simulates the performance of the SAV system in the City of Lisbon, with simplified transportation network, travel demand from local travel survey (International Transport Forum, 2015). The link level travel speed also varies by time of the day in this model. In certain scenarios, ITF model also incorporates dynamic ride-sharing into consideration. Spieser et al. (2014) explore the scenario where SAV system will serve all travel demand in Singapore, given the car-sharing business model. They model travel behavior based on local transportation survey and taxi database and a graph-based presentation of local transportation network with link level speed estimated based on Singapore's taxi database. Rigole (2014) envisions a future in which SAVs serve all the home-based work trips, given the ride-sharing business model of the system in the City of Stockholm. A New York Automated Mobility on Demand (AMOD) model replaced all taxis with autonomous vehicles to serve the existing taxi travel demands with New York network (Shen & Lopes, 2015). The results suggest that even without dynamic ride-sharing the SAV can outperform the conventional taxi mode by optimizing the vehicle dispatching component in the system.

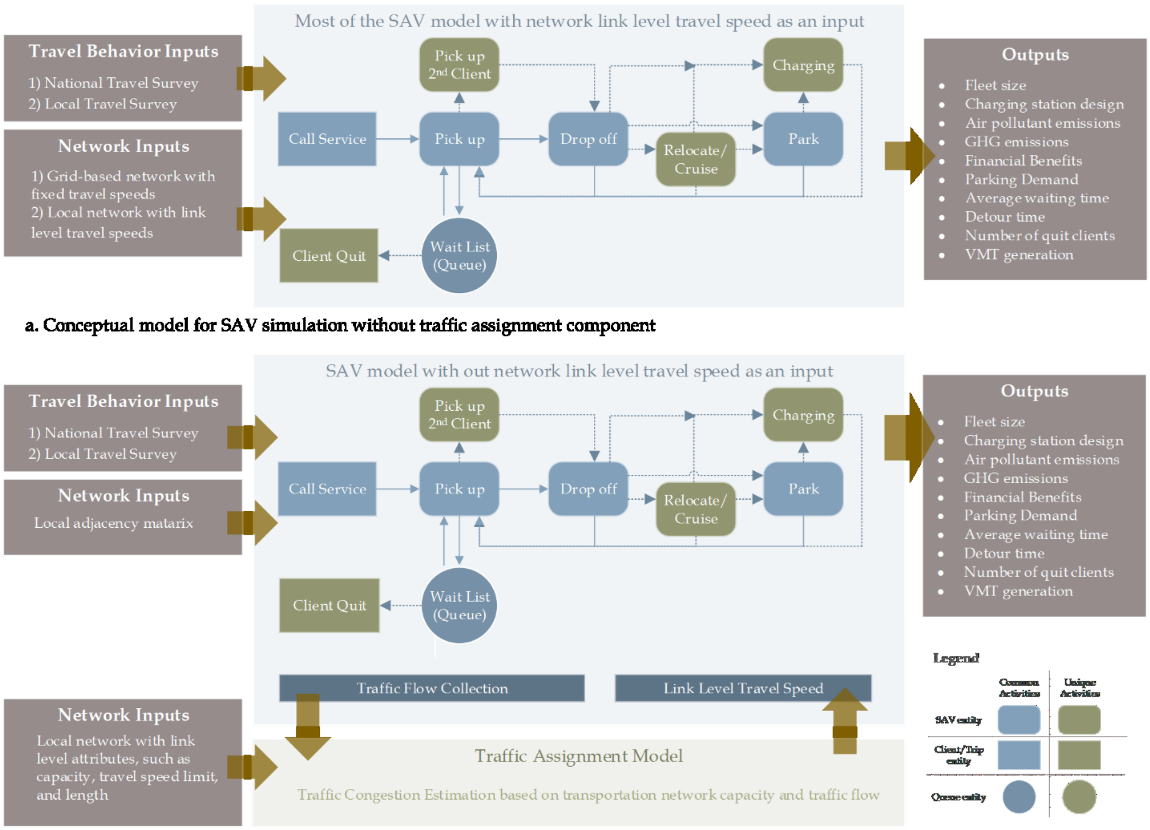
In summary, the existing SAV models do share features regarding model inputs, system behavior, modeled entities, and model outputs, as tabulated in Table 2. The SAV models have two major model inputs: travel behavior inputs and network inputs. Almost all of the models used either local or national level of travel survey data as an input to model travel behavior in the simulation. The network input vary slightly based on the travel behavior input and the model framework. Most studies using national travel survey, such as National Household Travel Survey (NHTS) from the U.S., as the travel behavior input adopt grid-based transportation network input. Meanwhile, empirical studies tend to use local transportation network as the network input. Depending on whether traffic congestion is considered in the simulation, various local transportation network features are used in the model. Models without traffic congestion components usually require link level travel speed by time of the day as a model input, while models with traffic congestion/trip assignment component require more specific network inputs including link level capacity, length, and speed limit.

The existing models also share many system activities or behaviors. For instance, all the models incorporate activities, such as call service, client pick up, drop off, and park behavior, in the simulation. These activities are considered as essential components of the SAV system, without which the operation of the system will be hindered. Some simulation studies incorporated more activities in the model, including vehicle relocation, cruise, dynamic ride-sharing, vehicle charging, and client quitting, to tailor the models to achieve their simulation objectives.

The modeled entities are also quite similar across studies, as all the models included entities, such as trip/client, SAV, and queue in the simulation. Trip or client entities generate travel demand such as trip origins, destinations, and departure time. SAV entities are controlled via a vehicle allocation module to deliver calling clients to destinations. Clients are put into a waiting list or queue if all SAV are busy. These entities form the basic structure for the SAV system. Some studies also added charging station entities into the model to determine their spatial distributions.

Despite similar model activities and entities, the models, however, have dramatically different outputs, including fleet size determination, charging station distribution, environmental impacts, operation costs, parking demand, system service quality, and etc. The studies collect, analyze, and summarize these simulation outputs as a function of various modelled activities in the simulation. For instance, environmental impacts such as GHG emissions and VMT generation are calculated based on the delivery routes and speed of vehicles in the model. The demand of parking space is the maximum of all parking demand at certain location throughout the simulation day.

From the conceptual model perspective, there are two types of framework for SAV models, as illustrated in Figure 2. One type of framework considers level of travel speed as an exogenous input of the model and traffic congestion is not actually modelled in the SAV simulation; the other type of model framework incorporates trip assignment module into the simulation framework, so that traffic congestions patterns can also be simulated in the model. The second type of model framework is useful for studies whose primarily model purpose is to examine traffic flow related topics, including, but not limited to, traffic congestion, infrastructure capacity design, and transportation energy consumption.



a. Conceptual model for SAV simulation without traffic assignment component

b. Conceptual model for SAV simulation with traffic assignment component

Figure 2: SAV simulation conceptual models

Table 2: Existing SAV Model Contents and Structure Summary

Study	Business Model	Model Endogenous Inputs		Exogenous	Model Entities			Model	Model
		Travel Behavior	SAV parameters	Inputs	Transient	Resource	Queue	Activities	Objective(s)
Ford (2012)	CS	Local travel survey	Fleet size	Grid network	Client	SAVs	-	Pick-up, drop-off	System demands determination
Kornhauser (2013)	CS	Local travel survey	Fleet size	Grid network	Client	SAVs	-	Pickup, drop-off	System demands determination
Burns et al. (2013)	CS	Assumed trip generation rate	Fleet size	Grid network Constant speed	Client	SAVs	Wait List	Pickup, drop-off, dispatch	Economic costs analysis
Fagnant & Kockelman (2014)	CS	Assumed trip generation rate	Fleet size Peak and off-peak speed	Grid network	Client	SAVs	Wait List	Pick-up, drop-off, dispatch, relocation	Environmental impact analysis
Spieser et al. (2014)	CS	Singapore travel survey Singapore Taxi data	Fleet size	Singapore network, Link level speed	Client	SAVs	Wait List	Pickup, drop-off, dispatch	Fleet size determination, Financial benefits analysis
Rigole (2014)	CS DRS	Stockholm commuting travel data	Fleet size Travel speed	Stockholm network	Client	SAVs	Wait List	Pick-up, drop-off, dispatch, trip match, trip assignment	Fleet size determination, Environmental impact analysis
Chen (2015)	CS	Assumed trip generation rate	Fleet size Peak and off-peak speed	Grid network	Client	SAVs Charging Stations	Wait List	Pick-up, drop-off, dispatch, relocation, charge	Charging station location choice
Fagnant & Kockelman (2015)	DRS	Austin travel demands model	-	Austin network	Client	SAVs	Wait List	Pick-up, drop-off, dispatch, trip match, relocation, trip assignment	Fleet size determination, Financial benefits analysis
Fagnant et al. (2015)	DRS	Austin travel demands model	-	Austin network	Client	SAVs	Wait List	Pick-up, drop-off, dispatch, trip	Fleet size determination,

Study	Business Model	Model Endogenous Inputs		Exogenous Inputs	Model Entities			Model Activities	Model Objective(s)
		Travel Behavior	SAV parameters		Transient	Resource	Queue		
								match, relocation, trip assignment	Service quality analysis
Zhang et al. (2015)	CS DRS	Assumed trip generation rate	Fleet size Peak and off-peak speed	Grid network	Client	SAVs	Wait List	Pick-up, drop-off, dispatch, trip match, cruise, park	Urban parking demands analysis
ITF (2015)	CS DRS (2+ trips)	Lisbon travel survey Synthetic population	Fleet size	Lisbon network, Hourly link level speed	Client	SAVs	Wait List	Pick-up, drop-off, dispatch, relocation, trip match, park	Fleet size determination, Impact on traffic volume, Vehicle use, Parking demand
Shen & Lopes (2015)	CS	NYC Taxi data	Fleet size	NYC Open street network	Client	SAVs	Wait List	Pick-up, drop-off, dispatch	Vehicle dispatching methods analysis
Chen et al. (2016)	CS	Assumed trip generation rate	Fleet size Peak and off-peak speed	Grid network	Client	SAVs Charging Stations	Wait List	Pick-up, drop-off, dispatch, relocation, charge	Charging station location choice

Note: *CS*, car-sharing; *DRS*, dynamic ride-sharing

3.1.1.2 Model Activity Implementation Algorithms Review

This section revisits the algorithms used to implement various activities in the SAV simulation model. The reviewed activities include travel behavior, vehicle dispatching, dynamic ride-sharing, and vehicle relocation.

3.1.1.2.1 Travel Behavior Model

The existing literature can be divided into two streams: 1) studies that simulate travel behavior without actual local travel survey data and 2) studies that mimic travel pattern given local travel survey or taxi data. The first method can be useful when the origin and destinations (OD) matrix is not accessible. These models are sufficient to determine the average performance of the system given the national normalized travel demand. While the second approach is more robust to explore the performance of SAV system within the local context.

Many hypothetical studies recreate travel demand based on national trips characteristics, such as trip generation rates per household, trip departure time distribution, and trip length distribution (Chen et al., 2016; Fagnant & Kockelman, 2014; Zhang et al., 2015a). These studies assign trip generation rates to each grid cell in the hypothetical city. The model then randomly generate trips that originate in each cell based on the assigned trip generation rate, assuming that trip generation follows Poisson process, which is an assumption adopted in many transportation simulation studies. The trip generation rate is usually higher in the predefined urban core area and diminishes as the distance to urban core increases. The trip generation module then randomly assigns a destination for each generated trips based on trip length distribution and the general direction of the trips.

During daytime, the trip generation module will be more likely to push trips into core urban area. While in the evening, the module tends to drive trips back to other places. In this way, the total number of trips entering and leaving downtown area can be balanced throughout the day.

Some other studies focus on implementing SAV system in the real-world context generate trips entities using a slightly different method. Some obtain OD matrix from regional transportation demand model and recreate trips given the OD pairs throughout the simulation day (Fagnant & Kockelman, 2015b; Fagnant et al., 2015; International Transport Forum, 2015; Spieser et al., 2014). The OD pairs usually have the resolution at designated travel zone level. Shen & Lopes (2015) generate trips based on the New York taxi data, which are geocoded with pairs of longitude and latitude.

In summary, the existing literature modeled travel behavior based on the assumption that people's travel pattern will not change after the introduction of SAV system. However, there is a difference in the market penetration of SAV model, i.e. the percent of trips that will be served by SAVs: the Singapore study assumes that SAVs will replace all vehicles; studies in Austin assume that SAVs will only serve approximately 10% of local trips; the Lisbon study splits trips by modes such as SAVs, private AVs, and transit, using a mode choice model.

3.1.1.2.2 Vehicle Dispatching Model

The vehicle dispatching model includes rules regarding how to assign SAVs to serve calling clients. Most of the existing models assign vehicles based on first come first serve principal. The New York study, so far, is the only one that explores the impact of different vehicle dispatching algorithms on the performance of the system. The model tested three scheduling strategies: 1) no-scheduling strategy, 2) static-scheduling strategy and 3) online-scheduling strategy. The no-scheduling strategy is similar to the first come first serve rule applied in most of the other studies. Based on this strategy, the system always assigns the closest idle SAV to serve the incoming client. In static scheduling strategy, the model does not only search for idling vehicles but also busy ones. For idling vehicles, the model will estimate waiting time, based on the location of the calling client. For occupied vehicles, the model sum the predicted the remaining service time and the empty rerouting time as the potential waiting time. The model then dispatches the vehicle, either busy or idle, with the shortest waiting time to the client. The online-scheduling strategy is similar to the static-scheduling strategy except that the model updates potential waiting time given traffic delays and updates vehicle dispatching results. Simulation results suggest that there is no significant difference in average waiting between the first two scheduling strategies. However, the online-scheduling strategy reduces potential waiting time by approximately 20%. The last dispatching algorithm, however, requires more computational power.

3.1.1.2.3 Dynamic Ride-sharing Model

Dynamic ride-sharing model matches clients with similar itinerary together to share rides, if both clients are willing to share. There are two elements in trip matching algorithms: 1) trip characteristics constraints and 2) cost split strategies. It is only feasible to combine trips with similar origins, destinations, and departure time together. Additionally, given the condition that all the agents in the models are perfectly rational, most existing studies assume that ride-sharing will only happen when the compensation (i.e. transportation cost reduction) of ride-sharing is greater than the marginal cost required to accommodate the driver and riders. There are also multiple ways to split costs among drivers and riders. The trip characteristic constraints typically consider the difference in departure time, arrival time, availability of seats, maximum detour time, and other personal preferences, such as gender and smoking. Agatz, Erera, Savelsbergh, & Wang (2011) imposed controls on the earliest departure time and latest arrival time to both drivers and riders. Some studies also incorporate spare seats availability into consideration. Baldacci, Maniezzo, & Mingozzi (2004) and Amey (2011) constrain the maximum excess travel time tolerable for participants. Dueker, Bair, & Levin (1977) added psychological components into the trip matching process. For instance, female participants may feel safer and prefer to share rides with other female participants. Some other studies recommend to include other personal preferences, such as smoking behavior, into the design of ride-sharing algorithm (Ghoseiri, Haghani, Hamedi, & Center, 2011). There are also multiple ways regarding how the travel costs, i.e. fuel, parking, and tolls, should be distributed among participants. Geisberger, Luxen, Neubauer, Sanders, & Volker (2009) suggest that costs be divided evenly among all ride-sharing clients. Based on such distribution principle, trips share similar travel direction, but significantly different trip length, may not be matched. Agatz et al. (2011) propose that fares be distributed based on the distance of individual trips. Kleiner, Nebel, & Ziparo (2011) formulate an auction-based system to benefit the drivers who offer vehicles. Such strategy can be useful during the peak hours, when the riders in the SAV system have to bid for rides.

3.1.1.2.4 Vehicle Relocation Model

There is a wealth of car-sharing program management studies regarding the design of various vehicle relocation models. Most of the studies suggest that vehicle relocation or rebalancing can significantly improve experiences of users, especially at stations where the demand usually exceeds supply without the relocation process (Barth, Todd, & Xue, 2004; Fan, Machemehl, & Lownes, 2008; Wang, Cheu, & Lee, 2010). Therefore, these studies suggest that vehicle relocation is a fundamental component to maximize the use of vehicles and minimize fleet size in the car-sharing program. The algorithms proposed in these studies, however, is not directly applicable in the SAV simulation models, as the relocation process in SAV system can be different from that in the conventional car-sharing system in two ways: 1) operators are not required in the SAV system and 2) the relocation destination is not limited to existing car-sharing stations. Most early studies in car-sharing industry review vehicle relocation strategies in a static setting (Barth et al., 2004). Fan, Machemehl, & Lownes (2008) develop a stochastic modeling method to determine vehicle relocation to maximize system profit based on the projected service demand at each rental station. Wang, Cheu, & Lee (2010) determine vehicle relocation based on forecasted traffic pattern and travel demand. Wang et al (2010) reallocate the vehicles from the anticipated surplus stations to under supplied stations. The transfers are made between stations with the smallest travel time cost, rather than the shortest distance.

Fagnant & Kockelman (2014) develop a vehicle relocation algorithm for the SAV system. The algorithm calculates balancing values for big zones in the hypothetical city to determine the potential relocation destination for idling vehicles located in SAV supply surplus areas. The imbalance value for each zone is estimated based on the following formula:

$$BlockBalance = SAVs_{Total}\left(\frac{SAVs_{Block}}{SAVs_{Total}} - \frac{Demand_{Block}}{Demand_{Total}}\right) \tag{1}$$

Given the calculated block balance value, several different vehicle relocation strategies are further tested. One strategy pushes vehicles in zones with 10% or more SAV surplus to zones with 10% or more SAV shortage. The second strategy estimates balance value for each grid and then relocate vehicles. The third approach assigns SAVs from zones where two or more vehicles are idling to zones where all vehicles are busy. The last strategy pushes vehicles in cells with three or more necessary idle vehicles into adjacent grid cells where the anticipated supply is low. The results suggest that the first strategy that operates at 25 big zone level in the region is the most efficient vehicle relocation method. Similar vehicle relocation strategies are also tested in Fagment & Kockelman's Austin model. Instead of dividing the city into 25 zones, the Austin model subdivides the cities into 2-mile by 2-mile blocks to estimate block balance values. The implementation results suggest that the relocation process can reduce the share of clients in 5-minute wait intervals by 82% and result in slightly smaller vehicle fleet size. Therefore, similar relocation strategy is applied in the design of the SAV simulation model for this dissertation.

3.1.1.3 SAV Model Assumptions and Simplifications Review

In this dissertation, the model simplifications are considered as "a choice among alternative ways of dealing with an aspect of the system under infestation and is focused on reducing complexity" and model assumptions are defined as "a 'knowledge gap', a deficiency in information that prevents progress at either the modeling or the simulation phases of the project” (Birta & Arbez, 2007). A summary of SAV model simplifications and assumptions are listed in Table 3.

Some studies apply simplifications to recreate travel behaviors, vehicle speeds, and SAV service priorities. The trips are generated based on simplified trip generation rates or local OD matrix. The origin and destination of the trips are simulated at the grid level or transportation analysis zone level to reduce location resolution and improve simulation speed. The link level travel speeds are simplified to be constant at specific time of the day based on travel assignment model outputs. Additionally, in the majority of the models the assignment of SAV is simplified to follow the first come first serve principal.

Many existing studies make assumptions towards SAV costs and client's tolerance. Currently, the system is not implemented yet; hence, there is "knowledge gaps" regarding how expensive the SAV fares will be and how long are people willing to wait for services. Therefore, the SAV fares are assumed to be $0.5-1 per minute in some studies (Fagnant & Kockelman, 2015; Zhang et al., 2017). In some simulation studies, clients are assumed to leave the system after waiting for more than 10-15 minutes (Fagnant & Kockelman, 2015; Zhang et al., 2017), which are usually the headway for transit systems. While, in other studies, the clients are assumed to never leave the system. Some assumptions are not explicitly stated in the literature. For instance, most studies assume that the travel behavior will not change when the SAVs are available, i.e. there will be no significant variations in the distributions of trip frequency and trip length.

Table 3: Existing SAV models assumptions and simplifications

Business Types	Study	Simplifications	Assumptions
car-sharing models	Burns et al. (2013)	Random and uniformly distributed trip origins and destinations Peak hour factors applied to mimic congestion Vehicle travel speed is constant (30mph) One type of vehicle used for all trips Clients are first come first served	Travel time value = \$0.05 per mile (\$1.5 per hour) Time value = \$0.85 per mile (\$25 per hour)
	Fagnant & Kockelman (2014)	Trip generation rates based on NHTS data, directional effects by time of the day Constant vehicle travel speed for peak (21 mph), and off-peak hours (33 mph) Types of vehicle used are similar to the national profile Clients are first come first served 5-min time step	Relocation strategies
	Spieser et al. (2014)	Trip generation rates based on local OD matrix Vehicles serve based on shortest path on the road network Clients are first come first served Exchange rate of 1.25 SGD/USD Average travel speed to vary periodically based on time of the day	Four people effectively share a single shared autonomous vehicle (for analysis) Vehicle has to show up within 5 minutes, otherwise expand fleet size Market penetration level = 100%
	Chen (2015) Chen et al. (2016)	Trip generation rates based on NHTS data, Directional effects by time of the day Quarter-mile gridded 100-mile by 100-mile region Constant vehicle travel speed for peak and off-peak hours Clients are first come first served Best relocation strategy based on Fagnant & Kockelman (2014) 5-min time step	SAV priced between \$0.75 - \$1.00 per mile Electric vehicles have an 80-mile-range Charge stations are level II charging infrastructures \$25,000 per-vehicle automation costs Market penetration level = 10%

Business Types	Study	Simplifications	Assumptions
	Shen & Lopes (2015)	Origins and destinations based on NYC taxi data Clients are first come first served	Different passenger dispatching algorithms SAV maximum speed is 25 mph SAV Load capacity is 4
ride-sharing models	Rigole (2014)	Home-based work internal trip generation only (~60% of all trips) Travel speed determined by trip assignment model in Matlab, given the link level Capacity and density function Intra-Zonal travel time = $\sqrt{area_{taz}}/(2 * travel\ speed)$	Lifetime of SAVs = 30,000 km Lithium-ion battery lifetime = 2000 charging cycle Passenger load time = 2 min| unload time = 1 min SAV Load Capacity is 4 Less than 10% of detour time allowed
	Fagnant & Kockelman (2015) Fagnant et al. (2015)	Clients are first come first served 2-mile blocks within 12-mile by 24-mile area Link level travel speed obtained by feeding OD matrix to Maksim trip assignment model	SAV purchase costs $70,000 SAV fare = $1.00 per mile Excessive trip time <= 20% of trip duration without ride-sharing Market penetration level = 10%
	Zhang et al. (2015)	Trip generation rates based on NHTS data, directional effects by time of the day Constant vehicle travel speed for peak (21 mph) and off-peak hours (33 mph) 0.2-mile gridded 10-mile by 10-mile city Clients are first come first served 5-min time step	Vehicle cruising time Clients agree to ride-sharing only when benefits can be gained (reduced travel costs vs. Increased time costs)
	ITF (2015)	Trip generation based on 200-meter by 200-meter cells Three types of SAVs with different capacity Cars follow the shortest path Link level travel speed based on trip assignment model	Battery charging time = 30 minutes Electric vehicle's mile range is 175 mile per charge Excessive trip time <= 20% of trip duration without ride-sharing Mode splits among different options

3.1.1.4 Model Paradigms Review

There are three paradigms, namely system dynamics (SD), discrete-event simulation (DES), and agent-based modeling (ABM) and each is characterized by a set of core assumptions and some underlying concepts to describe the world (Behdani, 2012). Despite most of existing SAV simulation modeling efforts embraced the ABM paradigm, as discussed in the previous section, it remains critical to compare the three standards with the simulation objective of this work to determine the choice of appropriate simulation paradigm and to guide the conceptual model development process.

The SD approach tends to present the world from a "top-down" angle, which focuses on system level observables. The atomic components in SD models are aggregated state variables. The SD models are structured based on "feed-back loops". The aggregated state variables are updated simultaneously given the positive of negative feedback loops among the variables. Time is considered as incremental or continuous in models based on SD paradigm. Therefore, this modeling paradigm is most appropriate when the entities in the system are homogeneous or at least share similar features and there will be no micro-level of entities in the system. This paradigm is most frequently applied in qualitative analysis to support long-term strategic decision-making process (Brailsford & Hilton, 2001), and therefore, no SAV simulation, to date, embrace this simulation paradigm.

The DES and ABM models, on the other hand, represents the world from a "bottom-up" perspective. In DES and ABM models, time increases discretely rather than continuously. In both approaches, heterogeneous entities are presented in models. The DES models are usually labeled as more "passive," while the ABM approach is characterized as more "active". Nevertheless, neither of them is considered as an absolute better worldview and therefore, should be utilized given their strengths and limitations.

The DES approach, the most widely applied paradigm in the operation research, mimics the real-world systems with distinct and chronologically ordered events. The principle component of the model is "event", which changes the states of entities in the system and triggers other consequential events in the system. DES focuses more on the modeled system and, therefore, is a more appropriate approach to use when the simulated system, per se, rather than the entities who are being served, is the primary concern of the study.

The ABM attempts to recreate individuals, also known as "agents", and their interactions between each other and the environment. The ABM approach is usually characterized by autonomous, i.e. agents make their decisions without a central controller, and reactivity, i.e. agents adapt their behavior given changes in the environment and other agents. Therefore, ABM is the most appropriate paradigm to use when examining the interactivity and adaptively among agents and environment is the objective of the model.

Most of the existing SAV simulation models employ the ABM paradigm (Chen, 2015; Chen et al., 2016; Fagnant & Kockelman, 2014, 2015b; Fagnant et al., 2015; Zhang et al., 2015a). However, it appears that interactions between different types of agents, SAV agents and client agents, are not the primary concern in the simulation model. Travel behaviors of client agents do not evolve in the model; in other words, clients will continue their initial travel pattern regardless the performance of the system, which is quite "passive". Therefore, ABM may not be the ideal model paradigm given the current limited understanding regarding people's reaction towards the proposed SAV system. Some other studies recommend and construct models based on the DES paradigm to examine the operation of SAV system (Levin, Li, Boyles, & Kockelman, 2016; Shen & Lopes, 2015), as it will be easier to adapt SAV simulation model to include traffic assignment module into the model framework.

3.1.1.5 Time Variable Review

Time variables are treated differently based on two worldviews in SAV simulation model, i.e. activity scanning worldview and event scheduling worldview. The activity scanning worldview based models separate system behavior into various activities and time advances in constant small steps. The model increment time with a small step and then evaluate the preconditions of all activities and process in the model to determine whether the state variables can be updated or not. For instance, many time-step based models used such world view (Chen, 2015; Chen et al., 2016; Fagnant & Kockelman, 2014, 2015b; Fagnant et al., 2015; Zhang et al., 2015a). The fundamental shortcoming of this worldview is the inefficiency of the time advance mechanism, i.e. how to define time steps in the model.

The event scheduling worldview based models are formulated based on a set of future events. A future event includes “a scheduled event together with all conditional events that could be affected by the occurrence of the scheduled event”(Birta & Arbez, 2007). The time advances via using a future event list (FEL) and the simulation time is always updated to the time stamp of the event that is currently processed. Therefore, under this worldview, the model time advances discretely based on events, rather than constant small time steps. The model stops if a given condition is satisfied or there are no events in the FEL. Some SAV models do not include time step designs seem to adopt this worldview for more refined time resolution in the model (International Transport Forum, 2015; Shen & Lopes, 2015). Compared with the activity scanning world view, the event scheduling worldview presents the advantage of reduced simulation time and coding complexity (Birta & Arbez, 2007). In summary, this work will use event-scheduling worldview to advance time variable in the model.

3.1.2 SAV Discrete Event Simulation Model

Builds upon the review of current SAV simulation models, this sections describes the formulation and development of a discrete event based SAV simulation model. This model is used to address the proposed three research questions.

3.1.2.1 <u>SAV Model Entities and Activities</u>

In the SAV system, there are four types of entities. These include: 1) the vehicle entity, 2) the trip entity, 3) the queue entity and 4) the parking lot entity. All entities in the model will get involved in a sequence of activities. For each trip entity, the model schedules a *call event* at the trip departure time. When handling the call events, the system dispatches the vehicle with the least trip cost and schedules a *pickup event*. If the vehicle assignment process fails, the trip entity will be put on a waiting list, i.e. the queue entity. After picking up a client, the vehicle either *picks up* a second client (if ride-sharing can be established) or schedule a *drop-off event* upon arrival at the trip destination. If a busy vehicle becomes empty, the system will schedule a *relocation event* to balance vehicle distribution, if necessary. If a vehicle remains idling after relocation (or after drop-off in case relocation was not triggered), the system schedules *find park event* to identify a parking lot entity, which minimizes the total parking cost, and eventually schedules a *park event* upon arrival. The *move events* are scheduled to transfer the vehicles to another location or to a parking lot. The *move events* can be terminated if the moving vehicle is assigned to serve incoming trips. The life cycle diagrams in Figure 3 illustrate the sequence of events that trip and vehicle entities may go through in the simulation.

3.1.2.1.1 Call Event

At the beginning of each simulation day, the model generates trip entities based on the local OD matrix and a recent travel survey. Assuming that the trip generation follows Poisson Distribution (Fagnant & Kockelman, 2014), the model simulates the total number of produced trips for each OD pair i and j by generating a Poisson random number given the average trip number, $\lambda_{i,j}$, from the local OD matrix.

$$NumTrip_{ij} = Random.Poission(\lambda_{i,j}) \tag{2}$$

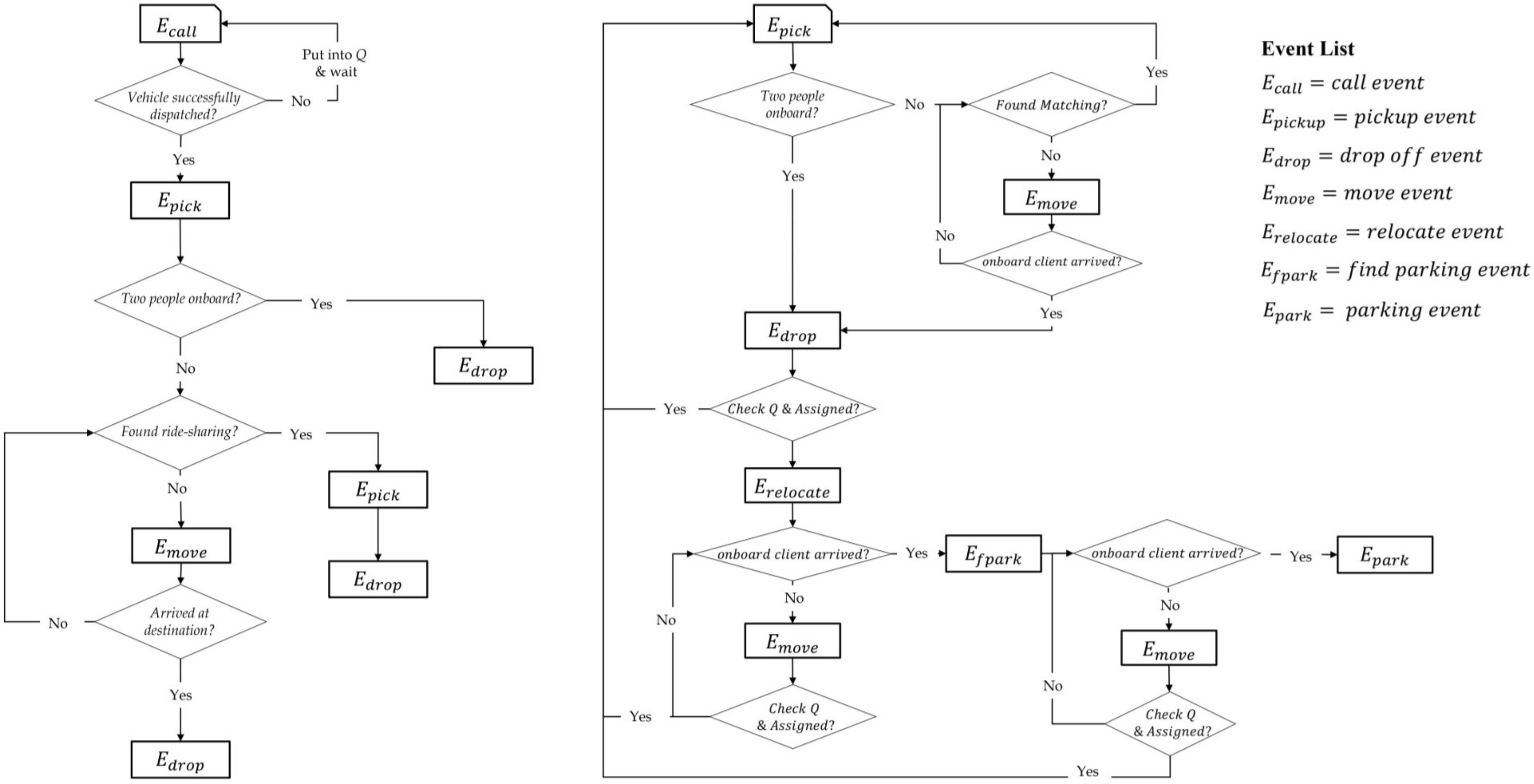
For each generated trip k, the trip departure time is assigned based on the formula below. The Cumulative Density Function (CDF) for trip departure time is estimated based on the weighted local travel survey.

$$DepartureTime_k = CDF_{dt}^{-1}(r) \tag{3}$$

where,

r, is uniformly distributed random number from 0 to 1.

$CDF_{dt}^{-1}(r)$, is the inversed CDF for trip departure time.



a. Life cycle of trip entities

b. Life cycle of vehicle entities

Figure 3: Life-cycle diagrams for the client (left) and vehicle (right) entity in the SAV system

For each generated trip entity, the model schedules a call event at trip departure time *dt*. Upon the occurrence of the call event, the system dispatches SAVs to fulfill the travel demand. The system searches for SAVs whose status is not "busy" and assigns the one that offers the lowest costs, including both time and fare costs to serve.

$$Assigned\ SAV_j = \min_{j \in J_A}(time\ cost_j + fare\ cost_j) \tag{4}$$

Where,

j is the index for vehicle;

J_A is a set of indices for vehicles whose status is not "busy";

$time\ cost_j$ is the potential excessive travel time cost if j^{th} vehicle was assigned;

$fare\ cost_j$ is the anticipated fare cost if j^{th} vehicle was assigned.

The time cost is calculated based on the assumption that the waiting time is valued as half of people's hourly wage (Zhang et al., 2015b). In the ride-sharing process, the vehicle does not operate on the first come first serve basis but optimize the route to minimize VMT. In return, each client can benefit from 40% reduction in SAV fare.

$$time\ cost_j = 0.5\ T_i.salary * \left(picking\ up\ waiting\ time_j + detour\ time_j\right) \tag{5}$$

$$fare\ cost_j = \begin{cases} \$0.5 * deliverty\ time_j, & no\ ride - sharing\ established \\ \$0.3 * deliverty\ time_j, & if\ ride - sharing\ is\ established \end{cases} \tag{6}$$

Ride-sharing will only be established if the following criteria are satisfied.

1. The excessive time for both trips is equal or smaller than 15% of travel time without ride-sharing;

2. For short intra-zonal trips, the acceptable maximum detour time is set as 3 minutes;
3. The ride-sharing induced detour time should be compensated by the decrease in SAV fare for both clients.

If a vehicle is assigned, then the status of the vehicle will be updated to "busy". A pickup event will be scheduled at the estimated arrival time at the trip origin. Meanwhile, the system frees up a parking space if the vehicle was parked. The trip will be put on a waiting list if the system fails to arrange service.

3.1.2.1.2 Pickup Event

In the pickup event, the vehicle picks up the waiting client and then updates system states based on the vehicle occupancy. If there is only one onboard client, then the status of the vehicle becomes "one available", the path will be updated to the shortest path to deliver the client, and a move event will be scheduled to push vehicle towards the destination. If the vehicle picks up a second ride-sharing client, then the status of the vehicle changes to "busy" and the path will be updated to the shortest path to serve both clients. A drop-off event will be scheduled for the client who should be dropped off first given the updated path.

3.1.2.1.3 Move Event

The system handles a move event based on the status of the vehicle. If the status of the vehicle is "one available", the system will try to find potential ride-sharing. For the other types moves, such as relocating or parking vehicles, the system attempts to assign the vehicle to serve the closest waiting trip. Once assigned for service, the vehicle become "busy" and a pickup event will be scheduled. If the vehicle is not assigned for service and has not arrived at its destination, the vehicle moves onto the next node in the network towards the destination. If the vehicle has arrived at the destination, the system schedules drop-off, find parking, or park event for "one available", "relocating", or "parking" vehicles separately.

3.1.2.1.4 Drop-off Event

In this event, the vehicle drops off the client who has arrived at the destination. After dropping off the client, if the vehicle becomes empty, the status of the vehicle changes to "available" and a relocation event will be scheduled. Otherwise, if there remains onboard client, the system schedules another drop-off event.

3.1.2.1.5 Relocate Event

The primary goal of the relocation event for j^{th} vehicle is to balance the spatial distribution of available vehicles to reduce average waiting time. This event builds on the existing SAV relocation algorithm (Fagnant & Kockelman, 2014) to relocate the vehicle from surplus zones to underserved areas. For each zone the imbalance value is calculated using the formula below:

$$Imbalance_i = \left(\frac{SAVs_i}{SAVs_{Total}} - \frac{Demand_i}{Demand_{Total}}\right) / \frac{Demand_i}{Demand_{Total}} \tag{7}$$

where,

i is the index for zones;

$SAVs_i/SAVs_{Total}$ is the share of available SAV in zone i

$Demand_i/\ Demand_{Total}$ is the share of travel demand in zone i.

If the vehicle is in a zone with imbalance value larger than 10%, then the system allocates the vehicle to zone j where the imbalance value is the smallest in the service area, updates relocating path, labels the vehicle as "relocating", and schedules a move event. Otherwise, the system directly schedules a find parking event.

3.1.2.1.6 Find Parking Event

In the find parking event, the status of the vehicle will be labeled as "parking". The zone with the lowest potential parking cost, calculated using the formula below, will be identified as the parking destination for the vehicle. In the time-based charging scenario, the potential parking cost is the product of expected parking time and the hourly parking price. The expected parking time matrix is initiated using averages from free-parking scenario and is updated every 10 minute. After determining the parking destination, the system updates the path for the vehicle, reserves one parking space at the destination and schedules a move.

$$P_{TAZ} = \min_{k \in K_A} (fuel\ cost_{i,k} + parking\ cost_k) \tag{8}$$

$$parking\ cost_j = \begin{cases} 0, & Free\ parking\ scenario \\ entrance\ price_k, & Entrance - based\ charging\ scenario \\ hourly\ price_k * hour_{k,t}, & Time - based\ charging\ scenario \end{cases} \tag{9}$$

Where,

i is the zone index for the current location of the vehicle;

k is an index from a set K_A which contain all zones where parking space remain available;

$hour_{k,t}$ is the anticipated parking time at zone k and time t.

3.1.2.1.7 Park Event

In the park event, the j^{th} vehicle's status will be changed to "parked". There will be no other changes to the states of the system, until the vehicle is assigned again to serve incoming calls.

3.1.2.2 Model Inputs and Outputs

There are several inputs for the model, including transportation infrastructures, local travel demand, local income distribution, and SAV fleet size, among others, to assign values for attributes of different entities. Local transportation infrastructure data provides information about road network composition, link level travel speed by time of the day, and parking inventory, including the number of spaces and prices. The local OD matrix, and travel survey offers information regarding the trip origins, destinations and departure time. The primary model outputs include the spatial and temporal patterns of parking demand, i.e., the number of times that SAVs park, and parking space, i.e., the amount of parking land needed to accommodate the parking demand, as well as other metrics for service quality. The parking demand and space available are calculated using the formula below. The first simulation day is excluded, as it is used to determine the SAV distribution at the beginning of the day (Fagnant & Kockelman, 2014).

$$ParkingDemand_{d,t} = \sum_{i=1}^{N} ParkingDemand_{d,t,i} \tag{10}$$

$$ParkingDemand_{t} = \sum_{d=2}^{D} ParkingDemand_{d,t} /(D-1) \tag{11}$$

$$ParkingSpace_{i,d} = \underset{0 \le t \le 1440}{MAX} ParkingDemand_{i,d,t} \tag{12}$$

$$ParkingSpace_{i} = \sum_{d=2}^{D} ParkingSpace_{i,d} /(D-1) \tag{13}$$

where,

i is the index for zones and N is the total number of zones in service area;

d is the index for simulation day and D is the total number of simulation days;

t is the simulation time of the day (in the unit of minute).

3.1.2.3 Model Assumptions and Simplifications

There are several assumptions embedded in this model, listed as follows:

- 5% of the residents will give up their vehicles and use SAV system instead, which is similar to the assumption used in other studies (Burns et al., 2013; Fagnant & Kockelman, 2014; Zhang et al., 2015);
- There will be no induced travel demand after the implementation of SAV system;
- These residents are willing to share rides with strangers;
- The cost of SAV is \$0.5 per minute with no startup fees (Burns et al., 2013) and reduces to \$0.3 for ride-sharing client;
- The fuel cost for electric SAV is \$0.04/mile (Corwin et al., 2016);
- The clients leave the system after waiting for more than 15 minutes.

For easier model implementation, the following simplification are adopted in the simulation model:

- The trips start and end at TAZ centroids;
- The vehicle travel speed is fixed on a certain road segment and updated for AM peak, mid-day, PM peak, and night time periods;
- The average intra-zonal travel time is modeled using the following formula:

$$intra - zonal\ travel\ time = \frac{\sqrt{area_{taz}}}{2 * travel\ speed} \tag{14}$$

- Both loading and unloading times are set as 1.5 minutes;
- The clients will not cancel the trip after vehicle assignment (within a 15-minute waiting time);
- The clients are first come first served during off-peak hours;
- Available vehicles will serve the closest trip on the waiting list to optimize use.

3.2 Residential and Firm Location Choice Model

The widely used McFadden's MNL model (1978) is applied to estimate the preference for residential and firm locations. Different spatial units are used to estimate location choice models for home and businesses separately, because of the various availability of data sets. Disaggregated MNL model, i.e., the housing unit or property level model, is used to determine preferences for home location. Rather than exhausting all the alternative properties on the market, the model randomly samples 29 properties, denoted as C', from the entire choice set C as the modelled choice set. McFadden (1978) suggests that consistent estimations of coefficients can be achieved with a random sampling of all potential choices. Together with the selected property, there are 30 alternatives to choose for each household. Therefore, the probability of a household n choosing any property/alternative i in the residential MNL model can be expressed as:

$$P_{ni} = \frac{e^{V_{ni}}}{\Sigma_{j=1}^{30} e^{V_{nj}}} \tag{15}$$

The utility of household n choosing property i, denoted as V_{ni}, in the above equation can be written as a linear combination of various independent variables as follow:

$$V_{ni} = \beta_1 \boldsymbol{T_{ni}} + \beta_2 \boldsymbol{Z_i} + \beta_3 \boldsymbol{X_{ni}} + \boldsymbol{\epsilon_{ni}} \tag{16}$$

where, $\boldsymbol{T_{ni}}$ is a vector of commuting cost for household n at the property i. $\boldsymbol{Z_i}$ is a vector of property attractiveness measures, such as features of property i and characteristics of the built environment/neighborhood where the property i is located. $\boldsymbol{X_{ni}}$ represents interaction terms of socio-economic and demographic characteristics of household n with the attractiveness of property i. β_1, β_2 and β_3 are vectors of estimated coefficients. $\boldsymbol{\epsilon_{ni}}$ is unobserved random utility components for each decision maker i given the property n. This component is independent and identically Gumbel-distributed (McFadden, 1978).

The aggregated MNL model, i.e., the TAZ level model, is applied to reveal preferences for firm location. Given the larger sample size in the firm location choice model, nine TAZs with commercial or industrial land are randomly selected as alternatives for each firm in the model. In this model, the probability of a firm n choosing to locate in TAZ i can be expressed as:

$$P_{ni} = \frac{e^{V_{ni}}}{\Sigma_{j=1}^{10} e^{V_{nj}}} \tag{17}$$

The utility of firm n choosing TAZ i, denoted as V_{ni}, in the above equation can be expressed using a linear combination of a sequence of independent variables as follow:

$$V_{ni} = \beta_1 \boldsymbol{HC_{ni}} + \beta_2 \boldsymbol{L_i} + \beta_3 \boldsymbol{X_i} + \boldsymbol{\epsilon_{ni}} \tag{18}$$

where, $\boldsymbol{HC_{ni}}$ is a vector of accessibility to human capital for firm n at the TAZ i. $\boldsymbol{L_i}$ is a vector of developable/rentable land in TAZ i. $\boldsymbol{X_i}$ represents other built environment, accessibility, fiscal condition, localization, and agglomeration features in TAZ i. β_1, β_2 and β_3 are vectors of estimated coefficients. Similar to the residential location choice model, $\boldsymbol{\epsilon_{ni}}$ is unobserved random utility components for each decision maker i given the TAZ n, which follows independent and identically Gumbel-distributed.

Unlike the conventional MNL model, the alternatives are randomly sampled in the region for both residential and firm location choice models. In other word, the same alternative for each firm may refer to different properties or TAZs in the region. Therefore, the model does not include alternative specific constant nor base alternative. Both residential and firm location choice models are implemented and configured in R software using the *mlogit* package (Croissant, 2010).

3.3 Residential and Firm Relocation Choice Model

The relocation choice model for households are implemented using Monte Carlo simulation method. The model determines where the households may relocate after the reduction in transportation costs. Meanwhile, agent based simulation method is used to capture relocation pattern for firms, as the location choices of firms depend not exclusively by land features, which alters after the emergence of SAVs, but also the relocation/location of other firms across industry sectors. Therefore, the firm relocation choice model is designed to be iterative over several years.

3.3.1 Residential Relocation Choice Model

The residential relocation choice model first updates the residential location choice model utility results using the new transportation costs, T'_{ni}, obtained from the SAV simulation model. The probability of selecting each alternative can be expressed as follow:

$$P'_{ni} = \frac{e^{V'_{ni}}}{\Sigma_{j=1}^{30} e^{V'_{nj}}} \tag{19}$$

$$V'_{ni} = \beta_1 \boldsymbol{T'_{ni}} + \beta_2 \boldsymbol{Z_i} + \beta_3 \boldsymbol{X_{ni}} + \boldsymbol{\epsilon_{ni}} \tag{20}$$

The new cumulative density function CDF_n for household n can be obtained by accumulating P'_{ni} across all alternatives. A distribution of new residential location choices is then generated using the Monte Carlo simulation approach as below.

$$r = random.uniform(\,) \tag{21}$$

$$new\ choice_n = CDF_n^{-1}(r) \tag{22}$$

where, r is a uniformly distributed random number ranging from zero to one. The new residential choice for household n can be simulated by plugging r back into the inversed CDF for household n. This process is repeated for several times to obtain a representative distribution of new choices.

3.3.2 Firm Relocation Choice Model

Unlike the residential location choices, the employment location choices are simulated using an agent based model. The major reason is that firms select location not only based on static features, but also on the location of other firms due to the agglomeration and localization phenomenon. For each simulation year, new firms are generated based on the control totals in the region and some existing firms are randomly selected to relocate in the region. The amount of relocation firm is calculated based on the average relocation rate for each industry sector. For each of the relocating or new firms a choice set of TAZs are randomly generated and utilities for each TAZ in the set are calculated using the updated independent variables and the coefficients from the employment locations choice MNL model.

$$P'_{ni,k} = \frac{e^{V'_{ni,k}}}{\Sigma_{j=1}^{10} e^{V'_{nj,k}}} \tag{23}$$

$$V'_{ni,k} = \beta_1 \boldsymbol{HC'_{ni}} + \beta_2 \boldsymbol{L'_{ni}} + \beta_3 \boldsymbol{X'_{ni,k}} + \boldsymbol{\epsilon_{ni}} \tag{24}$$

Where, $P'_{ni,k}$ is the probability for firm n to choice alternative i at simulation year k; $V'_{ni,k}$ is the utility of alternative i in simulation year k to firm n; $\boldsymbol{HC'_{ni}}$ is the accessibility of human capital for firm n locating in TAZ i after the introduction of SAVs, which does not vary by simulation year; $\boldsymbol{L'_{ni,k}}$ is the updated rentable square feet density in the era of SAVs; $\boldsymbol{X'_{ni,k}}$ is the updated localization effects at TAZ i for firm n in simulation year k.

A CDF of choosing different alternatives are then developed based on the utilities across all alternatives. Then the firm's new location is simulated by plugging in a uniformly distributed random number (ranging from 0 to 1) into the CDF.

$$r = random.uniform(\,) \tag{25}$$

$$new\ choice_{n,k} = CDF_{n,k}^{-1}(r) \tag{26}$$

where, r is a uniformly distributed random number ranging from zero to one. $new\ choice_{n,k}$ is the TAZ that firm n will relocate to in simulation year k.

After one year of the simulation, the TAZ level firm counts by industry sector will be updated to generate $\boldsymbol{X'_{ni,k+1}}$ to be used in the simulation of the subsequent year. This agent based employment relocation choice model is implemented using UrbanSim (Waddell & Ulfarsson, 2003).

CHAPTER 4. SAV AND URBAN PARKING

This chapter describes the integration of the discrete event based SAV simulation model and Atlanta parking inventory to examine how SAVs will influence urban parking land use. The study area for this research question is the City of Atlanta. The study area is constrained in the city boundary due to the availability of parking inventory data.

4.1 Model Implementation

4.1.1 SAV Parking Inventory Input

Atlanta, the capital city of Georgia, had an estimated population of 447,841 in 2013 and an area of 134 square miles. The city is highly car-dependent, with more than 92.2% of the commuting trips completed by automobiles (ARC, 2011). The latest downtown parking survey reveals there are 93,000 parking spaces in Atlanta Downtown (CAP, 2014). The parking space data is only available for the City of Atlanta.

The publicly accessible parking inventory is developed based on parking surface data from the City of Atlanta and the Downtown parking inventory from Central Atlanta Progress (CAP). According to CAP, the average parking area is approximately 300 square feet per space. The number of parking lots for the rest of Atlanta is approximated by dividing the total parking square feet in each TAZ with the average parking area per space. It is assumed that at a low market penetration rate, only 5% of the households will give up their private vehicle and use SAVs to travel in the city. Therefore, only 5% of total parking space in each TAZ is reserved for SAV uses, which provides the system with 25,000 parking spaces throughout the city.

Three parking charging scenarios are developed in this study: 1) free parking scenario; 2) entrance-based charging scenario, where SAVs have to pay every time entering the parking lots; 3) time-based charging scenario, where SAVs pay parking fees based on the time in the parking lot. The third scenario is the most expensive parking charging scenario, while the first is the cheapest scenario. The parking price is imputed based on the average land value from tax assessor data. TAZ land values are rescaled from $0 to $20 per entrance or $0 to $10 per hour as the final parking price. Figure 4 illustrates Atlanta parking inventory inputs for different scenarios.

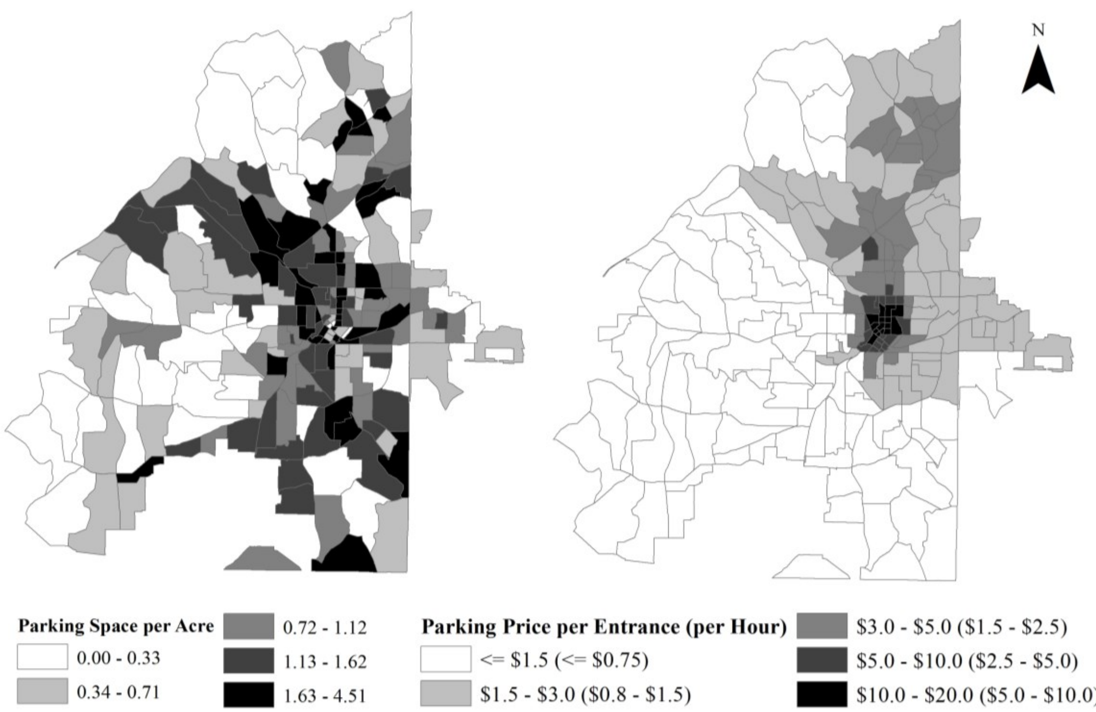


Figure 4: Parking Infrastructure Supply (left) and Parking Price Distribution (right)

4.1.2 Atlanta SAV Simulation Model Environment Settings

The spatial unit of the simulation is set to be Traffic Analysis Zones (TAZs), which is the same as the resolution of the vehicle trip Origin-Destination (OD) matrix prepared by Atlanta Regional Commission (ARC). Given that the parking inventory is only available in the City of Atlanta, the simulation model is implemented within the city boundary limit to determine the variations in parking demand. There are 208 TAZs in the City of Atlanta. At the market penetration of 5%, the system serves around 32,365 trips, which both start and end in Atlanta, on a typical weekday. The Atlanta road network with link level travel time for AM peak, midday, PM peak, and night hours is also obtained from ARC. There are 3,708 nodes and 8,694 edges in the transportation network.

Different fleet sizes are tested from 700 to 1,200 with an increment of 100 vehicles, and it is found that 1000 vehicles are sufficient to serve the population, with no client leaving the system. The model is then set to run for 50 consecutive simulation days for each scenario. The same string of random number is used in all scenarios to ensure that the differences in outputs are not caused by noise rising from the random number generator.

4.2 Model Results

4.2.1 Total Parking Demand and Parking Space

Simulation results from different scenarios suggest that the parking demand and parking footprint of the SAV system peaks in the free parking scenario and is the lowest in the time-based charging scenario, when parking is most expensive. An SAV, on average, parks 20.6, 16.6, and 8.6 times in free, entrance-based charging, and time-based charging scenarios, respectively. Meanwhile, the total parking space required ranges from 2,424 or 2.4 space/SAV in free scenario, to 2,144 in entrance-based charging scenario, and eventually to 1,895 in time-based charging scenario. Therefore, the occupancy rate of the 25,000-reserved parking space is 7.6% to 9.7%. In other words, around 22,575 to 23,100 public parking space will no longer be needed after the introduction of SAVs. Compared with the total parking inventory (500,000) in the city, the SAV system can emancipate around 4.5% of the public parking land at a low market penetration level of 5%. Such results indicate that one SAV can remove more than 20 parking spaces via vehicle ownership reduction and vehicle occupancy improvement. In this study, the potential reduction in parking space at the home end is not incorporated, given the lack of residential parking garage inventory. The amount of parking land reduction can be even higher if the residential parking land reduction is also included in the analysis.

4.2.2 Spatial Distribution of Parking Land Use

The results from different scenarios suggest that the more expensive it is to park, the more parking land will concentrate in low-income neighborhoods, as presented in Figure 5. In the free parking scenario (see Figure 5.a), parking demand is the highest in major trip attraction zones, such as Atlanta Downtown, Midtown and Buckhead areas. In the entrance-based parking charging scenario (see Figure 5.b), the parking spaces shift from highly developed TAZs to west side communities, such as English Avenue, Bankhead, and Center Hill, where land value is lower. In the time-based charged parking scenario (see Figure 5.c), the parking spaces concentrates in southwestern and a few northern TAZs. These communities tend to have lower median income, higher concentration of minority population, and a lower average land value, as shown in Figure

3.d. Additionally, the results from both charged scenarios also suggest that SAVs will not park in urban fringe areas, as the summation of parking and vehicle travel costs is the lowest in TAZs that are adjacent to the urban cores rather than in the urban fringe areas. This is because land value decreases exponentially as the distance to employment centers increases, while the fuel costs rise at a slower but constant rate. In short, the charged parking policies relocate parking space into low-income communities, which may lead to equity issues, such as inefficient use of valuable land parcels in these areas. However, it may also offer opportunities for new infill development, as the SAVs will be more accessible to these neighborhoods, which indirectly improves their mobility.

4.2.3 *Temporal Distribution of Parking Demand*

Figure 6.a displays the total parking demand by time of the day from three scenarios, and the results suggest that there is no significant difference among them. The parking demand peaks during 1-3 AM when the travel demand is the lowest and bottoms during evening peak hours. However, the temporal distribution of parking demand changes significantly in TAZs with different land use types. To illustrate this phenomenon, the TAZs are coarsely reclassified into four types based on employment and household density. These four types are CBD, employment oriented, mixed use, and residential oriented TAZs (see Figure 6.b).

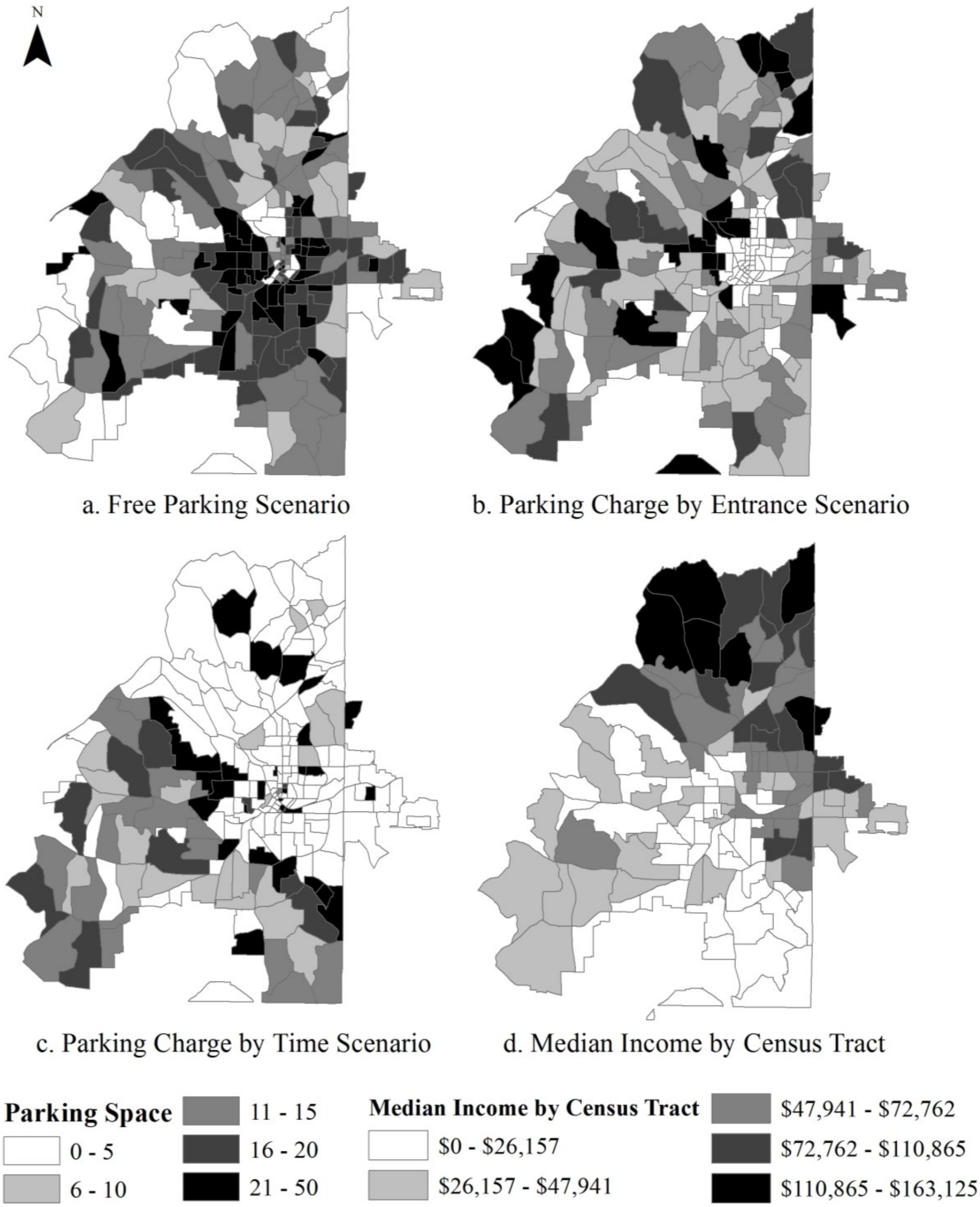
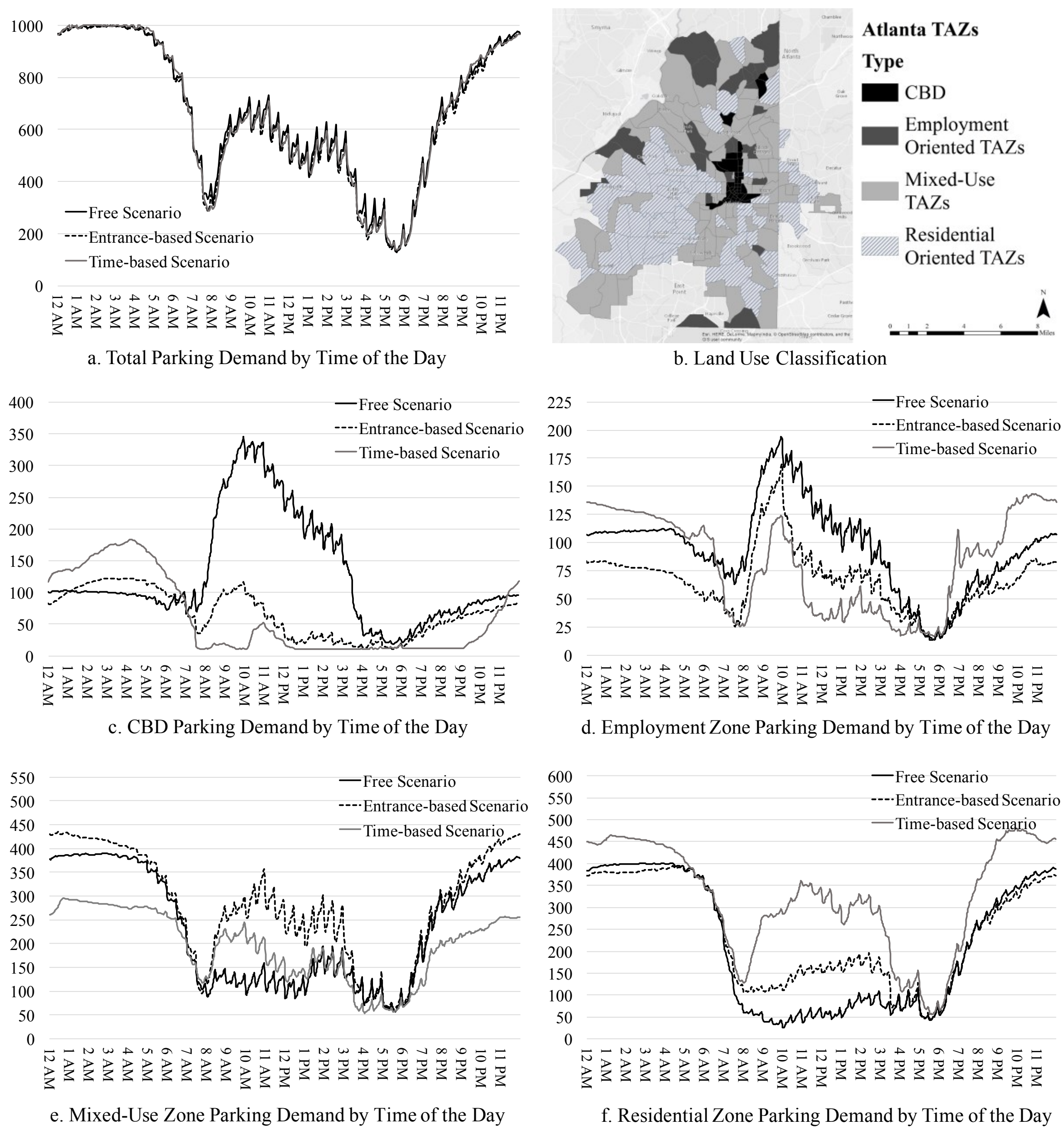


Figure 5*:* Spatial Distribution of Parking Spaces by Scenarios



a. Total Parking Demand by Time of the Day

b. Land Use Classification

c. CBD Parking Demand by Time of the Day

d. Employment Zone Parking Demand by Time of the Day

e. Mixed-Use Zone Parking Demand by Time of the Day

f. Residential Zone Parking Demand by Time of the Day

Figure 6 Temporal Distribution of Parking by TAZ Land Use Types

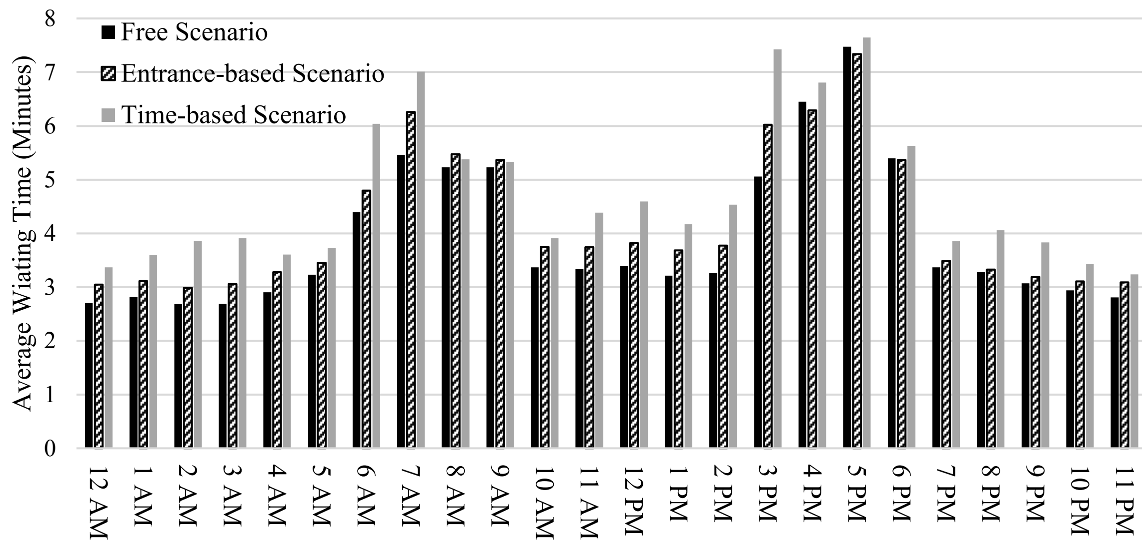
The parking demand in CBD areas declines dramatically in both charged parking scenarios, compared with free parking scenario, especially after the morning peak hours, see Figure 6.c. The required parking lots in the downtown area is reduced by over 70%

from 349 spaces in free parking scenario to around 102 or 51 spaces in entrance-based and time-based charging scenarios respectively. Similar parking demand variation patterns can also be found in employment oriented TAZs, as shown in Figure 6.d. However, the reduction in parking demand is not as large as the CBD areas, because the parking price is lower in the employment-oriented zones.

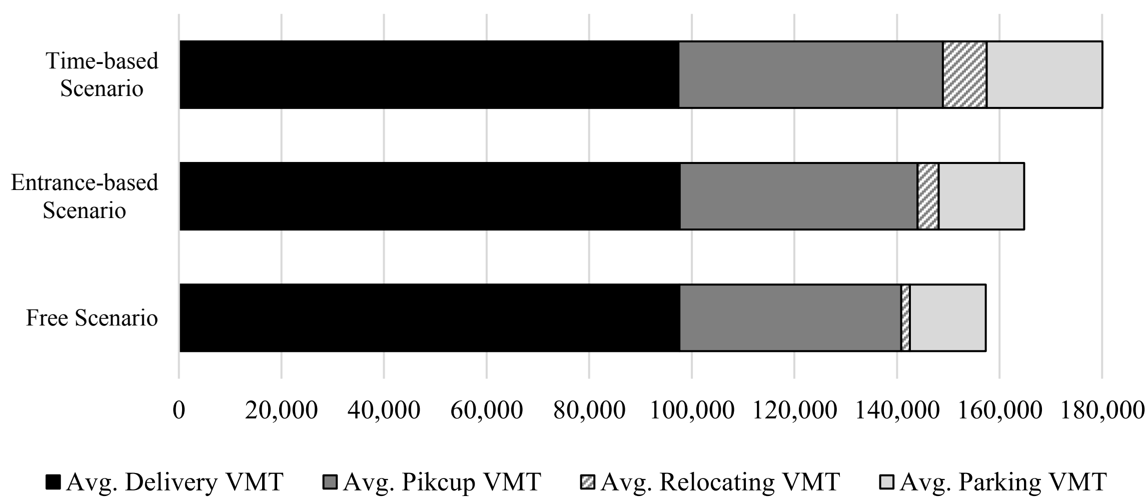
The reduced parking demand in CBD and employment oriented zones spills over into the mixed use and residential oriented neighborhoods. In the entrance based parking scenario, most of the parking demand relocates to the mix-use TAZs, see Figure 6.e. However, in the time-based parking charge scenario, even the mix-use TAZs are considered too expensive to park during midday and night time, when the average parking duration is longer. Therefore, most of the parking demand during these periods are pushed further into southern residential TAZs (see Figure 6.f).

4.2.4 Trade-offs in Waiting Time and VMT

In the charged parking scenario, the SAV system trades off parking costs with client's average waiting time and system VMT generation. Clients in the charged parking scenario wait longer, particularly at the beginning of the peak hours, such as 6-7 AM and 3-4 PM, as shown in Figure 7.a. In the charged parking scenario, vehicles tend to park at zones with lower land value, resulting in a spatial mismatch between vehicle and travel demand distributions. Compared with entrance-based scenario, vehicles in time-based scenario park further away from downtown result in even longer average waiting time.



a. Average waiting time by time of the day in different scenarios



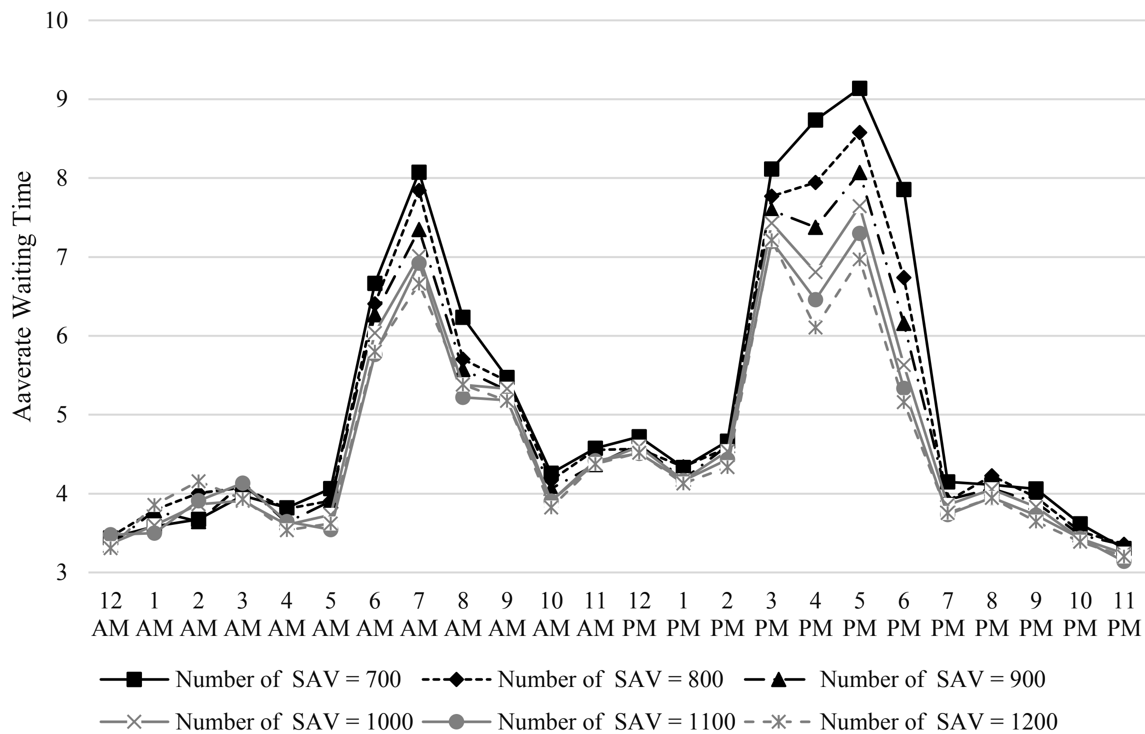
b. VMT generation by service types in different scenarios

Figure 7 Average Waiting Time (Top) and VMT Generation (Bottom) by Scenarios

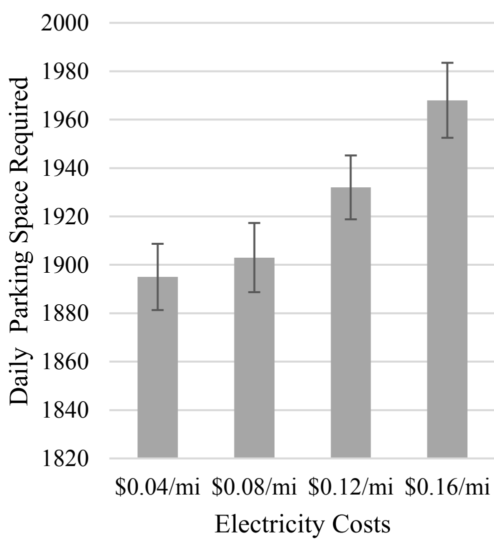
The VMT generation is significantly higher in both charged parking scenarios, as shown in Figure 7.b. The SAV system generates 158,308 VMT per day in free parking scenario. The VMT generation increases by 5% and 14%, respectively, in entrance-based and time-based charging scenarios. In summary, the SAV system accounts for increases in parking costs by increasing average waiting time and generating more VMT, both of which have negative social externalities. Therefore, policy makers need to design policies that combine empty VMT charges together with parking prices to reduce the negative environmental impacts, such as energy consumption and pollutant emissions.

4.3 Model Validation and Verification

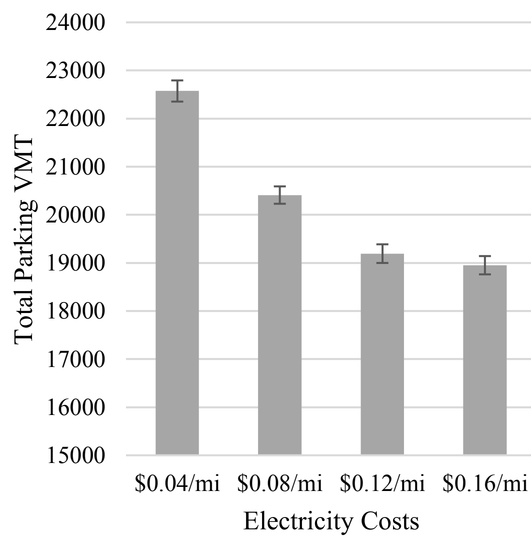
Ten alternative scenarios with different SAV fleet sizes ranging from 700 to 1200 and different SAV fuel (electricity) costs per mile base from \$0.04 to \$0.16 are tested to conduct elasticity test for the model. As shown in Figure 7.a, the average waiting time during peak hours, especially PM peaks, decreases with the increase in SAV fleet size, as expected. The decrease in average waiting time is significant at 7 AM and 4-6 PM, based on the t-test results (95% significance level, 2-tail test). The average waiting time does not change significantly during off-peak hours when there are adequate number of vehicles. The variation in total parking space and VMT generation for parking purpose are illustrated in Figure 7.b and c correspondingly. The results indicate that when fuel becomes more expensive, the SAV system consumes more parking spaces and generates less parking related VMT, as expected.



a. Average waiting time by time of the day and SAV fleet size



b. Daily parking space required by fuel costs



c. Daily Parking VMT generation by fuel costs

Figure 8 Elasticity Tests Results

4.4 Conclusions

The simulation results show that parking land use can be reduced by approximately 4.5%, once the SAVs start to serve 5% of the trips within the City of Atlanta in both charged and free parking scenarios. The results also reveal that each SAV can emancipate more than 20 parking spaces in the city. The reduction is achieved primarily through improving vehicle utilization intensity and reducing private automobile ownership. The results are consistent with the parking demand model based on the hypothetical grid based setting (Zhang et al., 2015) and the Lisbon SAV simulation study (International Transport Forum, (2015).

The simulation outcomes from charged and free parking scenarios suggest that charged parking policies can effectively reduce the amount of parking in the CBD areas. However, the demand for parking will be shifted to adjacent TAZs, resulting in larger VMT generation more congestion and longer average waiting time. Furthermore, results from the two charged parking scenarios suggest that when parking becomes more expensive; more parking demand is pushed into low-income neighborhoods, which may lead to social inequities. Therefore, policies to charge for parking need to be carefully considered to ensure that such adverse effects are minimized. Examples of such policies may include environmental impact fee for unoccupied VMT (i.e. relocation VMT and parking VMT) and innovative congestion fee on SAVs to restrict excessive VMT generation. Furthermore, the city may also propose smart parking policies, i.e. variable parking fee by time of day and by location of parking lots to reduce parking land use by improving the occupancy rate of the parking lots.

This study explores how the parking demand and parking land use may differ under free and charged parking policies. There remain some limitations regarding the design of the model, which deserves further explorations. To begin with, the parking destination choice is made only based on total parking price, while other factors including travel demand and vehicle distributions, are neglected. It will be ideal to design a parking lot searching algorithm that combine vehicle relocation and parking step together to minimize the operation costs of the system. Additionally, the model does not offer an optimized solution for urban parking land use design, which can be achieved by a centralized operation of SAV system and will provide a more comprehensive picture for smart city development. More studies should be devoted to examine how the SAV system can be integrated as part of the sustainable urban growth by optimizing urban parking land use via smart parking pricing policies. Finally, this model does not consider the environmental and social impacts of the tradeoffs between VMT generation, congestion levels, and parking space reduction, which is important for designing sustainable parking policies. Such tradeoffs can be examined with the help of models that include a trip assignment function that dynamically updates congestion at the road link level based on SAV travel patterns.

CHAPTER 5. SAV AND RESIDENTIAL LOCATION CHOCIES

This chapter first presents the methodology and data used to examine the variations in residential location choices after the introduction of SAVs, followed by results analysis. The model assumptions and configurations are verified using a series of elasticity tests. Finally, the primary findings in the shifts of residential location choices, policy implications, model limitations and future works are summarized in section 5.4.

5.1 Model Implementation

In this study, the framework used to examine the residential location choices in the era of SAVs is three-folded. First, a residential location choice model, as described in Section 3.2.1, is developed to reveal the existing preferences in home location by different market segment. The choices preferences include property level characteristics, such as number of bedrooms, size the property, built environment that the unit locates, as well as commute transportation costs, such as commute time costs, including both In Vehicle Travel Time (IVTT) and Out of Vehicle Travel Time (OVTT) costs, and vehicle operation costs, including ownership, insurance, maintenance and fuel costs. Second, the SAV model is applied to the entire 10-county Atlanta metropolitan area to obtain the average waiting time, i.e., OVTT at the TAZ level. The new commute costs for households are then calculated using outputs from the SAV model. Finally, the calculated SAV commute costs are plugged back into the residential location choices model to re-evaluate the utility for each alternative. The new location choices are then obtained using Monte Carlo simulation method, as described in Section 3.3.1. The methodology and data details for each step of the model are elaborated in the subsequent sections.

5.1.1 *Step 1: Residential Location Choice Model Implementation*

This section represents the implementation of a Multinomial Logit Model (MNL) to reveal workers' preferences in home location. The major data sources used to construct the dependent variables, i.e., home location choice, is described in section 5.1.1.1, followed by a description regarding the generation of various independent variables.

5.1.1.1 Data for location choice model

2011 travel survey collected by ARC and real estate property records from Zillow are innovatively combined together to substitute residential location choices, which is not available in the 10-county metropolitan area. The 2011 travel survey not only collects travel information, but also socio-economic and demographic information for 6,736 households with workers in the study area. The survey was conducted from November 2010 to January 2011. ARC has already geocoded the home location and office addresses for each sampled household. Therefore, the travel survey contains information regarding home location choice, socio-demographic, and economic information.

The survey, however, does not include information regarding when the household purchased the unit, at what price the property is purchased, nor the characteristics of the property. All the missing pieces are made up using data collected via Zillow Application Programming Interface (API). Zillow records are queried, accessed, and downloaded for each housing unit where the sampled household in the travel survey resides. Zillow records include property characteristics, such as the size the property, number of bedrooms, year built, property type, and etc. Additionally, Zillow also maintains historical transaction records for up to 10 years. It is already known that the sampled household resides at the unit by the time the travel survey is conducted (i.e., end of 2010). To live in the property, the family must have made the purchase at the closest transaction date in Zillow's transaction records before the travel survey. Based on such rational, information regarding property price and purchase date are collected.

After merging the ARC travel survey with Zillow records, some households are filtered out given the following criteria. First, it is noticed that there are time gaps between when the family purchase the property and when the socio-demographic and economic information are collected in the travel survey. To avoid dramatic changes in economic status and life cycle of the households, only households who purchased properties within the 5-year window are included in the final model. Second, households with unreasonable home location, office location, property values, and property characteristics are excluded. Moreover, workers who primarily telecommute are also excluded in the model, given that commute costs of this market segment does not vary by alternatives. Finally, workers who commute via MARTA or other local transit, occupying approximately 2.3% of the sample, are also removed. These households are excluded as it is the estimation for alternative transportation costs involves simultaneously modeling mode choice and home location choice. There is not sufficient empirical data to input into the model choice model as the SAVs are not implemented in the real-world. After this data cleaning and filtering process, there are 909 households left in the final model data set. These households, as shown in Figure 9, are evenly distributed in the study area.

The location choice alternatives are generated by randomly choosing from housing units that are transacted within the one-year time window for each sampled household. Properties that are sold/purchased six months before or after the real transaction date of the

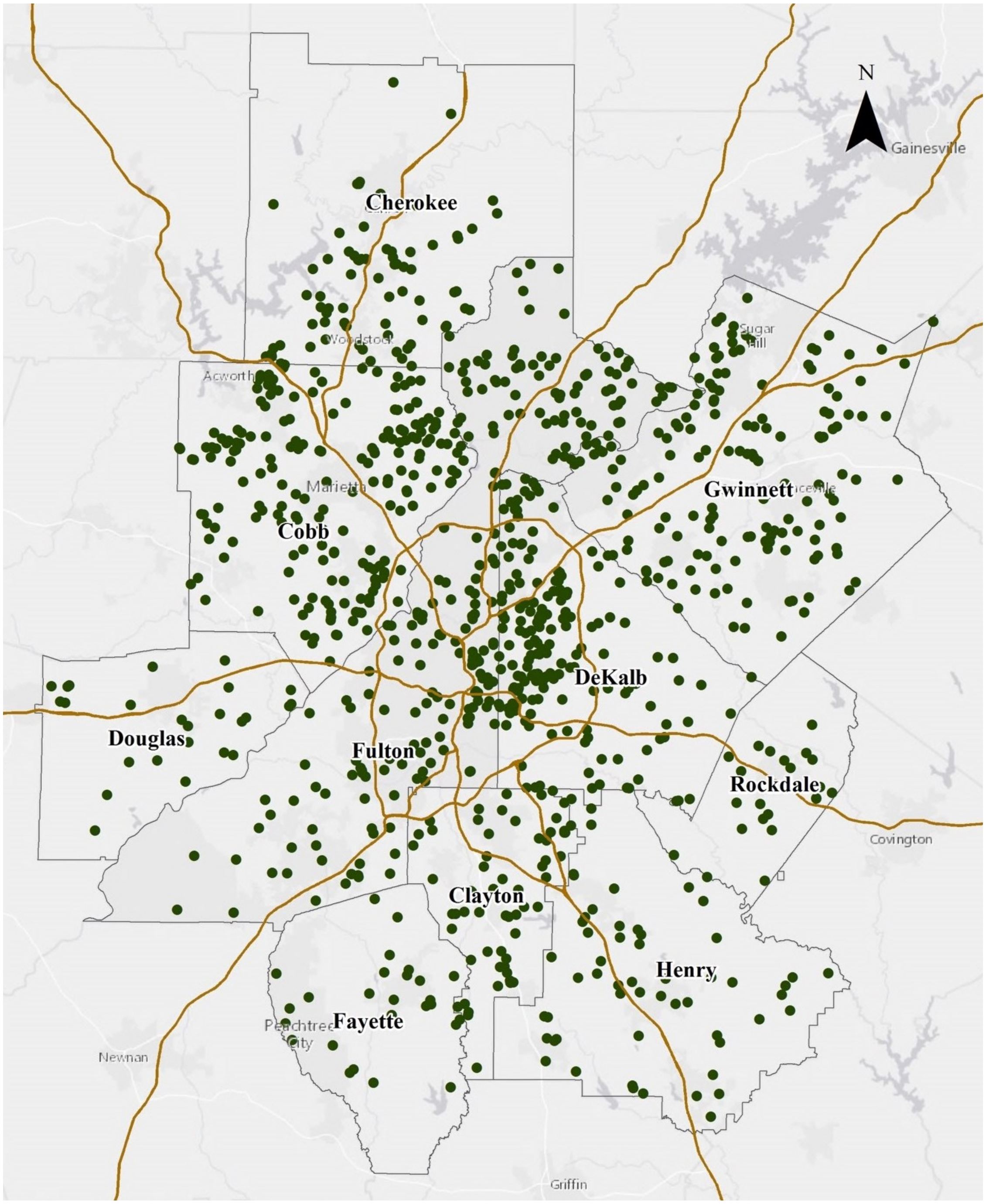


Figure 9: Spatial Distribution of Final Sampled Households

family are all included in a potential choice set. 29 alternatives are randomly drawn from this set, so that the estimated coefficients remain unbiased (McFadden, 1978). Eventually, there is 30 alternatives, including the chosen one, in the final Multinomial Logit Model.

5.1.1.2 Data for Independent Variables

The explanatory variables can be divided into four categories, including property characteristics, household socio-demographic and economic information, built environment variables, and commute costs. Property features and socio-demographic and economic information are obtained from Zillow and 2011 travel survey, as discussed in the previous section. The annual income variable from the travel survey is coded as categorical. Therefore, the household hourly salary is imputed by dividing the middle point of the income category by the total working hours per year. The built environment variables are collected from various sources. The quality of school districts IS measured using GreatSchools Ratings from Great Schools API. The TAZ level land use entropy index and population, and employment density are estimated using 2010 Census data and Longitudinal Employer-Household Dynamics (LEHD) data. The formula to calculate entropy index is as below:

$$entropy_i = -\frac{\sum_{j=1}^{5} p_{ij} * \log(p_{ij} + 0.01)}{\log(5)} \tag{26}$$

$$p_{i1} = \frac{h_{sf}}{h_{sf} + h_{mf} + job_{all}} \tag{27}$$

$$p_{i2} = \frac{h_{mf}}{h_{sf} + h_{mf} + job_{all}} \tag{28}$$

$$p_{i3} = \frac{job_{reserve}}{h_{sf} + h_{mf} + job_{all}} \tag{29}$$

$$p_{i4} = \frac{job_{prof}}{h_{sf} + h_{mf} + job_{all}} \tag{30}$$

$$p_{i5} = \frac{job_{labor\ intesive}}{h_{sf} + h_{mf} + job_{all}} \tag{31}$$

where,

i is the index for TAZ and j is the index for components in entropy index calculation;

h_{sf} is the number of single family household;

h_{mf} is the number of multi-family household;

job_{reserv} is the number of jobs in the retail/service sector;

job_{prof} is the number of jobs in the professional sector;

$job_{labor\ intensive}$ is the number of jobs in the labor-intensive industry.

In addition to the calculated built environment variables, the Walkscore at the block group centroid is also collected and tested in the model. All the built environment variables are spatially joined to properties using ArcGIS. The transportation costs variables are estimated using Equation 3-5 based on the worker's office location from Atlanta Travel Survey and alternative property locations from Zillow. In addition to the four types of explanatory variables, the mode also includes alternative specific interacted variables, such as property price income ratio, percent of same race in the neighborhood, and square feet per person.

Table 4 summarizes the detailed descriptive statistics for variables and the corresponding data sources. The descriptive statistics, shown in Table 4, are calculated based on the entire input dataset, which contains all alternatives for each household.

Therefore, the distributions of alternative specific variables do not reflect the true distribution of the variable in the real world. For instance, the average commute travel cost is $1,567 per month across all alternatives, which is significantly larger than the average commute travel cost for the eventually purchased properties, which is $1,155 per month.

Table 4: Summary of Independent Variables in Residential Location Choice Model

Variables	Type	Mean	Std. Dev.	Source
Socio-Economic Variable				
Household Header Age	Cont.	47.11	12.33	ATS
Household Size	Cont.	2.90	1.33	
Annual Income*	Cont.	$76,850	$35,510	
Vehicle ownership	Cont.	2.11	0.88	
# Worker	Cont.	1.62	0.59	
Race	Cat.	Range 1-9		
Life Cycle	Cat.	Range 1-10		
Property Variable				
# Bathroom	Cont.	2.88	1.05	Zillow
# Bedroom	Cont.	3.72	1.02	
Finished SQFT	Cont.	2524.54	1134.28	
Lot Size Acre	Cont.	0.52	0.66	
Age of Property	Cont.	19.49	21.18	
Sale Price	Cont.	$271,114	$178,410	
Sale Year	Cat.	Range 2005-2010		
Sale Month	Cat.	Range 1-12		
Single family (binary)*	Binary	92.94% Single Family		
Primary School Score	Cat.	Range 1-10		Great School
Middle School Score	Cat.	Range 1-10		
High School Score	Cat.	Range 1-10		
Built Environment				
Entropy Index*	Cont.	0.61	0.20	ACS, LEHD
Population Density (per mile^2)*	Cont.	2,503.87	2,524.55	LEHD
Employment Density (per mile^2)*	Cont.	917.35	2,048.02	
Reservation Job Density (per mile^2)*	Cont.	462.61	112.43	
Percent of Occupied	Cont.	0.92	0.05	ACS
Percent White	Cont.	0.58	0.28	
Percent Black	Cont.	0.30	0.29	
Percent Other	Cont.	0.12	0.10	
Median Income	Cont.	$71,907	$31,571	
Walk Score (Block Group level)	Cont.	34.36	35.21	Walk Score
Transportation Costs	Cont.			
Commute time costs (monthly)*	Cont.	$488.84	$429.26	Google, ATS
Commute travel cost (monthly)*	Cont.	$1,567.00	$1,028.67	
Interacted Terms	Cont.			
Property Price Income Ratio*	Cont.	4.58	8.51	Zillow, ATS

Variables	Type	Mean	Std. Dev.	Source
Percent Same Race*	Cont.	0.48	0.32	
Transportation Costs Income Ratio*	Cont.	0.38	0.55	
Finished SQFT Household Size Ratio	Cont.	1,114.72	864.43	

* indicating computed based on the source data
ATS: Atlanta Travel Survey; ACS: America Community Survey 2010 5-year estimates;
LEHD: Longitudinal Employer-Household Dynamics

5.1.2 Step 2: Independent Variables Updates

Different from the SAV simulation model used in the previous chapter, the model used to address residential location choice in the era of SAV is expanded to the 10-county region. The major inputs of SAV simulation includes 10-county OD matrices from the ARC travel demand model. There are 1593 TAZs and 9 million vehicle trips within the 10-county study area. The trip departure time distribution is obtained using the weighted 2011 ARC travel survey, as shown in Figure 12. The trip generation peaks between 7-8 am in the morning and 5-6 pm in the evening. The link level travel speed is also obtained from the ARC travel demand model. The link level travel speed differs by time of the day, such as morning peak, noon, evening peak and night to reflect congestion during peak hours.

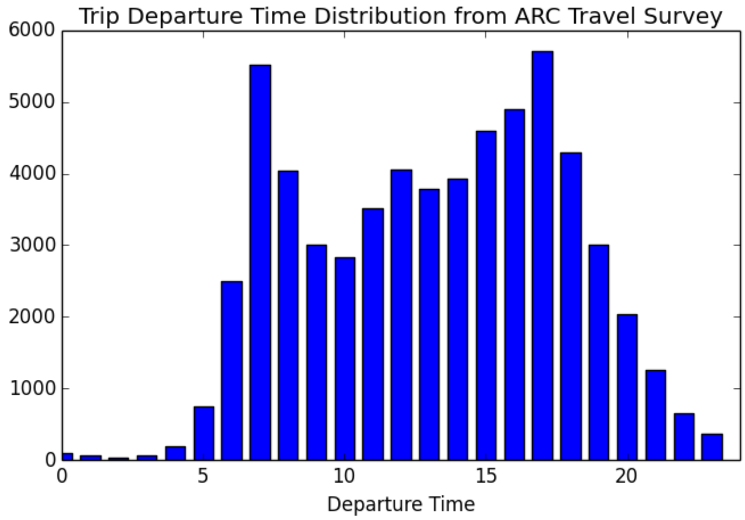


Figure 10: Trip Departure Time Distribution (weighted)

Results from 50 rounds of warm-up running tests suggest approximately 367,160 vehicles will be sufficient to serve 10-county travel demand to ensure that more than 99% of the clients can be picked up within 15 minutes after calling for services. The dynamic ride-sharing is not considered in the 10-county level SAV simulation to simplify the model structure and reduce model running time. The simulation results from the SAV simulation model for the city of Atlanta indicates the less than 10% trips can be matched together. Most of the dynamic ride-sharing incur during peak hours. The 10-county region is more sprawled than the City of Atlanta, rendering it even harder to match trips together. Therefore, excluding the dynamic ride-sharing service for the 10-county level simulation is not going to influence the daily average waiting time at the TAZ level significantly. The average waiting time is 7.13 minutes on a daily basis. The average waiting time increases to 10.59 during evening peak hours. Each SAV, on average, can serve around 24.5 trips on the daily basis. Additionally, adding more vehicles into the system is not going to improve the system performance significantly. An SAV system with 5% more vehicles (i.e. 18,358 more) can only reduce the all-day average waiting time by 0.32 minutes to 6.81 minutes. Therefore, for this study the total fleet size parameter is fixed at 367,160 vehicles for all simulation runs.

By the end of the simulation, average waiting time at the TAZ level is calculated across different model runs. The simulated waiting time is then used to update commute costs in the era of SAVs. After the introduction of SAVs, the commute time cost will no longer be the IVTT costs, but rather the OVTT at the origin of the trip, as the clients can multi-task in the vehicle. Therefore, the commute time cost for household n to choose alternative i can be re-estimated as the the sum of expected waiting time in TAZ i and TAZ k, where worker k's office is located, multiplied by the household hourly salary.

$$Commute\ Time\ Cost'_{ni} = \sum_{k=1}^{K} (WT_{taz_i} + WT_{taz_k}) * Salary_n \tag{32}$$

The commute travel costs are re-estimated by multiplying the total commute distance by the SAV cost per mile, as shown in Equation 8. The SAV costs per mile are approximated using results from various SAV costs simulation studies. In this study, the ¢30/mile fare is adopted to update commute travel costs in the SAV scenario.

$$Commute\ Travel\ Cost'_{ni} = \sum_{k=1}^{K} d_{n_k i} * SAV\ Cost/Mile \tag{33}$$

5.1.3 Step 3: Residential Relocation Choice Model Implementation

In this work, the residential relocation choice model is implemented in Python 2.7, based on model described in Section 3.3.1. The new location choices are randomly draw for 1,000 times to obtain representative distributions regarding the distance to CBD and distance to work. The new distributions are then compared to the current patterns to examine potential changes. Chi-square tests are conducted to determine whether the changes are statistically significant.

5.2 Model Results

5.2.1 Existing Residential Preferences

The entire population is divided into four market segments based on the household header's age (i.e. elder than 40 or not) and household life cycle (i.e. the presence of child). A chi-square test, as shown in Equation 33, is conducted for the pooled model and the market segment models, using all explanatory variables listed in Table 5.

$$Chi - square\ Test\ Score = -2\left(L(\hat{\beta}_{pooled}) - \sum_{g=1}^{G} L(\hat{\beta}_g)\right) \sim X^2_{(G-1)K,\alpha} \tag{34}$$

Where, $L(\hat{\beta}_{pooled})$ is the log likelihood for the pooled model, $L(\hat{\beta}_g)$ indicates the log likelihood for the g^{th} market segment. G indicates the total number of market segments. K is the total number of explanatory variables used in the models. α denotes the significance level of the test. The chi-square test score is estimated as 262.16, which is larger than $X^2_{36,0.05}(\approx 66.7)$. Therefore, the test is significant at the significance level of 5%. The significant chi-square test indicates the null hypothesis, i.e., the market segmented models is no better than the pooled model, can be rejected. Various configurations of market segments, such as groups by income level, by marriage status, and by age only, are also examined in this study. However, the chi-square tests for the other combinations of market segments turn out to be less significant or not significant at all. Therefore, these four market segments are adopted in this study.

The residential location choice model results, as shown in Table 5, indicate expected trade-offs between housing and transportation costs with respect to income, household size, and the presence of children. The statistically insignificant variables are removed from segment models. The model results suggest that all households prefer newer housing units, reflected in the negative signs of the coefficients across four models. The model also indicates households prefer housing units with lower prices, shorter commute time, and less total commute costs, as expected. Moreover, the percent of same race in the block group variable is positive and significant in all models, suggesting households self-select to settle in neighborhoods with similar race. Households with kids tend to live in better school districts and prefer single-family housing units. Elder households with kids also prefer suburban properties where the land use entropy index and population density is lower. In summary, the model results are reasonable, as the estimated coefficients have expected signs and significance level with respect to households' lifecycle. The models also have decent magnitudes of MacFadden R^2, ranging from 0.268 to 0.347. The community time costs and the ratio of commute vehicle costs and income in this model will be updated using the SAV simulation model outputs, as discussed in the following section.

Table 5: Residential Location Choice Model Results by Market Segment

	Age<40 & No kids [Beta]	Age<40 & Kids [Beta]	Age>=40 & No kids [Beta]	Age>=40 & Kids [Beta]
Property Age	-0.013 ** [-0.279]	-0.033 [-0.691] ***	-0.015 *** [-0.317]	-0.010 * [-0.232]
Sale price/Income	-0.226 *** [-2.926]	-0.252 [-1.538] ***	-0.318 *** [-2.778]	-0.220 *** [-1.533]
Percent same race (block group)	2.120 *** [0.658]	3.419 [1.074] ***	2.279 *** [0.720]	2.583 *** [0.818]
Commute time costs	-0.003 *** [-1.119]	-0.005 [-2.273] ***	-0.004 *** [-1.760]	-0.006 *** [-2.557]
Commute vehicle costs/Income	-5.541 *** [-4.299]	-5.121 [-2.577] ***	-6.284 *** [-3.130]	-1.761 ** [-0.968]
Middle school score (3,5]		0.623 [0.623]	0.447 * [0.447]	0.588 * [0.588]
Middle school score (5,7]		0.663 [0.663]	0.524 * [0.524]	0.764 * [0.764]
Middle school score (7,10]		1.011 [1.011] *	0.456 * [0.456]	1.254 *** [1.254]
Single family property (binary)		1.661 [1.661] **		1.229 ** [1.229]
SQFT per person				0.001 ** [3.650]
Land use entropy				-0.785 * [-0.157]
Population density				-0.0001 *** [-0.252]
N	149	144	306	310
Log Likelihood	-330.55	-290.69	-645.63	-681.05
Likelihood Ratio Test	242.24***	305.81***	554.67***	559.98***
MacFadden R^2	0.268	0.347	0.300	0.291

5.2.2 Transportation Costs in the Era of SAV

The SAV simulation results reveal that the average waiting time is negatively associated with the population and employment density in the TAZ, as shown in Figure 3. The spatial distribution of the average waiting suggest that people hailing for SAV service in more compact TAZs, i.e. TAZs closer to downtown and highway exists, will experience significantly shorter waiting time than people requesting service in suburban areas. The average waiting time in downtown and midtown neighborhoods is less than 5 minutes. Meanwhile, customers in the suburban areas in Cherokee, Douglass, Rockdale, Henry, and Fayette counties may expect longer than 10-minute waiting time. In other words, clients in denser area are more accessible to the SAV system compared to their suburban peers.

The new commute time costs are then estimated using the simulated average waiting time based on Equation 7. The updated commute time costs are approximately 77.1% less than the current costs. The reduction is most significant for longer commuting trips, as the only time costs left is the waiting time costs at the origin TAZs. The new commute travel costs are calculated with the assumption that SAVs fare will be $0.30/mile. The savings in commute travel costs are most significant for households with higher vehicle ownership and inefficient vehicles. The reduction in commute travel costs is, on average, 63.7%. Such reduction is based on the assumption that households are going to give up their private vehicles and rely exclusively on SAVs. The reduction can be less if the households still prefer to own one or two automated vehicles for non-commuting purposes. However, such scenario is not explored in this study. In summary, the SAVs can help reduce more than 72.5% of the total commute transportation costs for workers.

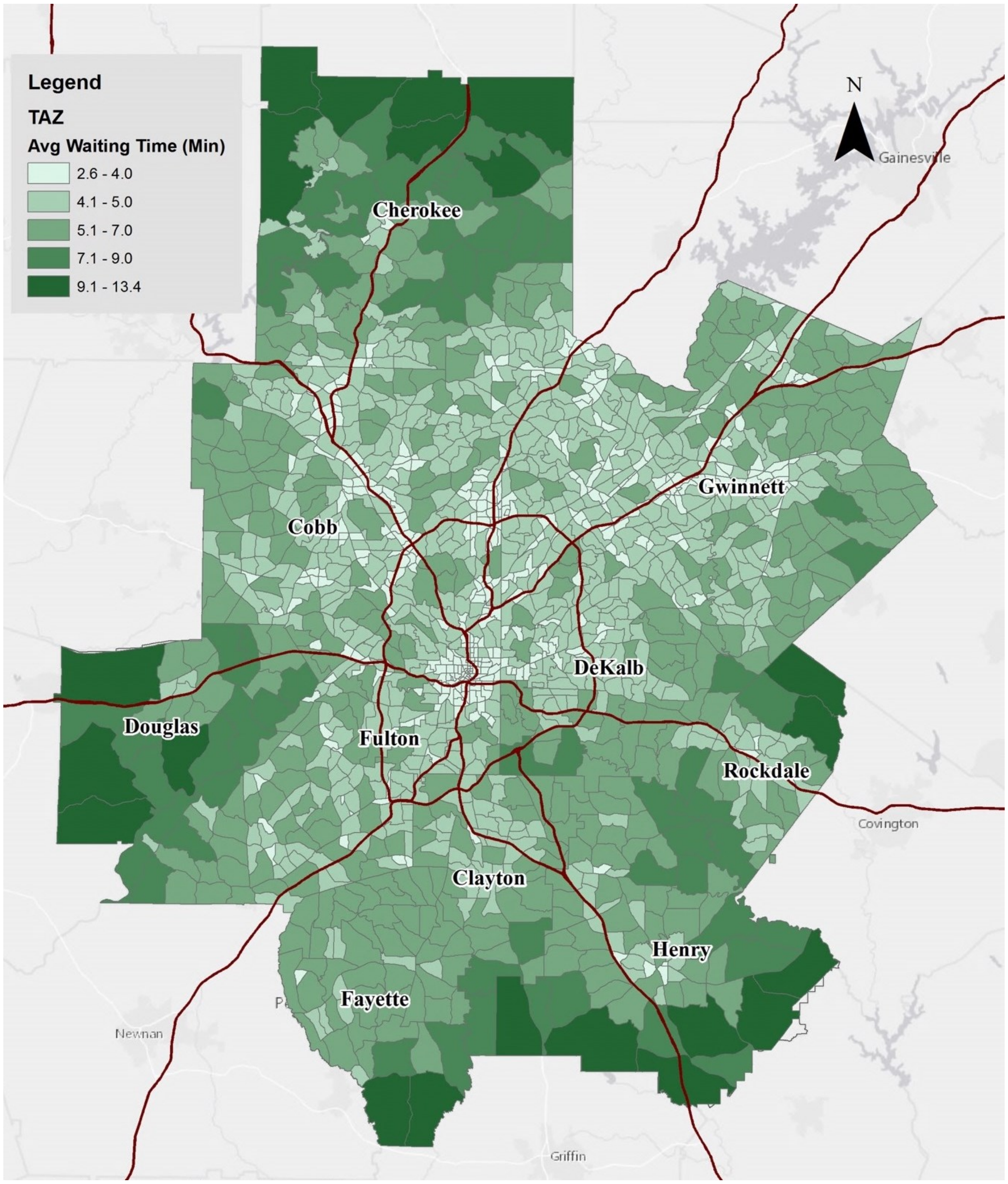


Figure 11: Average Waiting Time by TAZs

5.2.3 New Residential Location Choices

The Probabilities of choosing each alternative housing units are then re-estimated using the updated transportation costs variables. New residential location choices are simulated using the Monte Carlo method. The results are compared with the existing location choices by market segments, as displayed in Figure 13 - 16. All variations in distribution patterns are significant, according to chi-square test results.

Households, younger than 40 and without kids, on average, will relocate slightly away from the Central Business District (CBD). The existing median distance to CBD is around 16.71 miles, while the new median increases to 17.85 miles. This type of households tends to concentrate in areas, which are 20-25 miles away from downtown. Meanwhile less households will live within 5 miles or above 25 miles to the CBD area. Therefore, some households are moving away from downtown area to harvest the reductions in transportation costs and cheaper housings that are further away. Meanwhile, a portion of households would move slightly inward to avoid the large waiting time costs in the suburban area. The results also suggest that this type of households are going to live further away from their work locations, as the median distance to work per commuter increases from 28.09 to 34.67 miles.

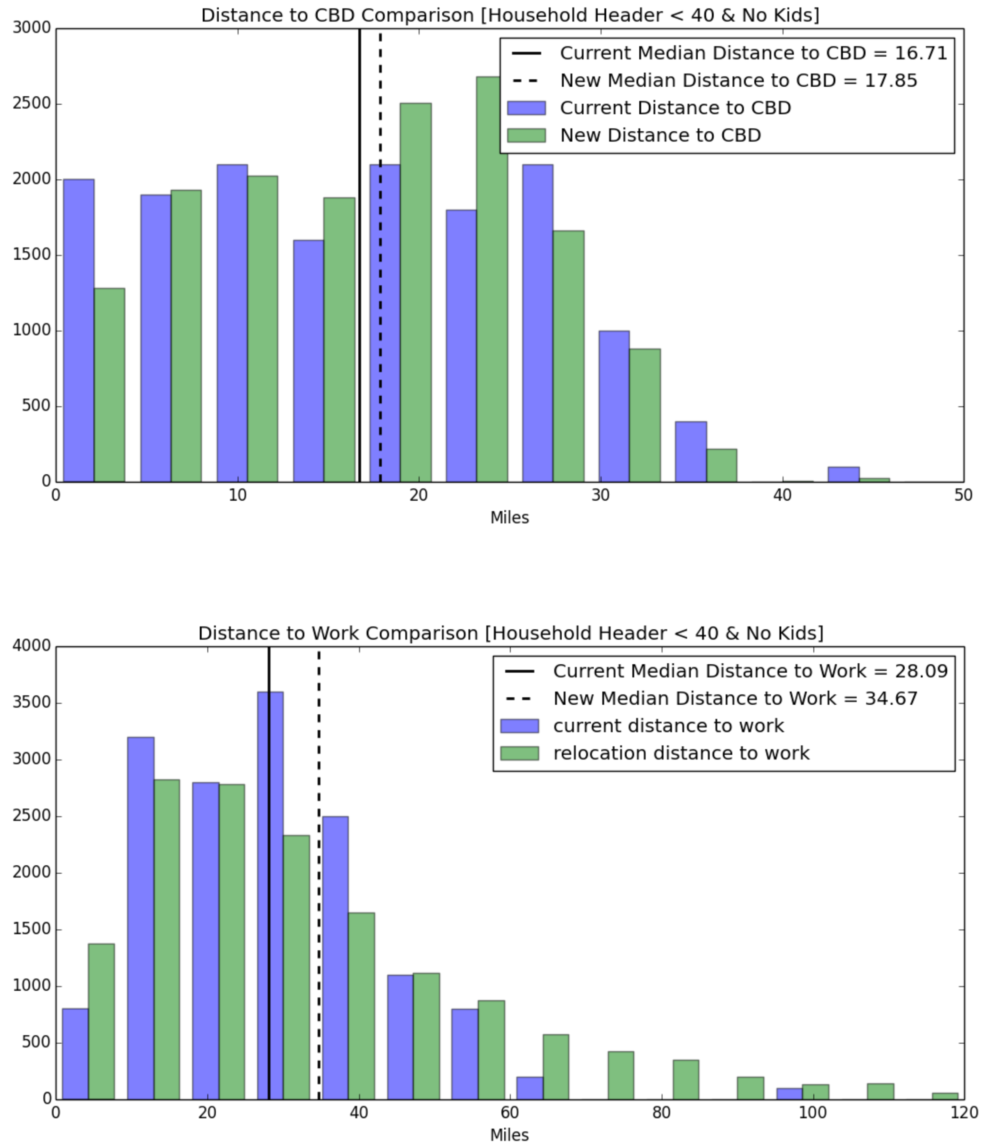


Figure 12: New Location Choices for Households Younger than 40 & No Kids

The general moving trend for households, younger than 40 and with the presence of children, is quite similar to their peers without kids. These commuters are also moving away from their current working given the reduction in commute costs. However, this type of households tends to move further away from CBD area to more remote areas that are more than 35 miles from the CBD area. This may be attribute to the fact that the public education resources in these areas are much better. Therefore, they are willing to accept higher overhead waiting time costs to benefit their children. The average school quality score for the selected housing unit increases from 6.6 to 7.1.

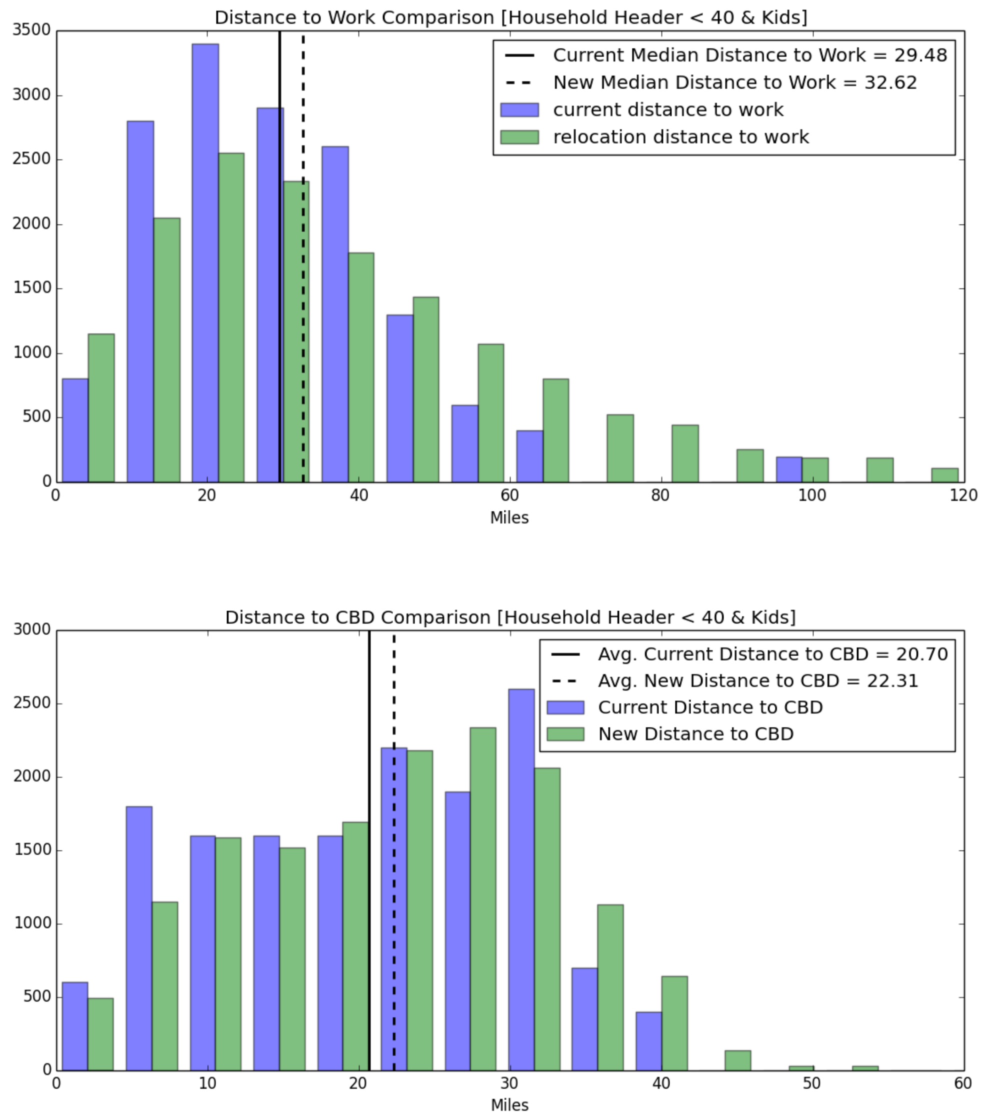


Figure 13: New Location Choices for Households Younger than 40 & Kids

Elder households without kids will also move away from their offices in the SAV scenario. However, different from their younger peers, elder households will relocate slightly closer to the CBD area, from 18.36 to 17.94 miles, as shown in Figure 5. Properties located within 10 miles to the CBD area will be more appealing to these type of households, due to the smaller waiting time costs in these TAZs. This market segment will also move approximately 3 miles further away from their working places for cheaper and newer properties. The median ratio of price of the housing units and income decreases from 5.3 to 4.5.

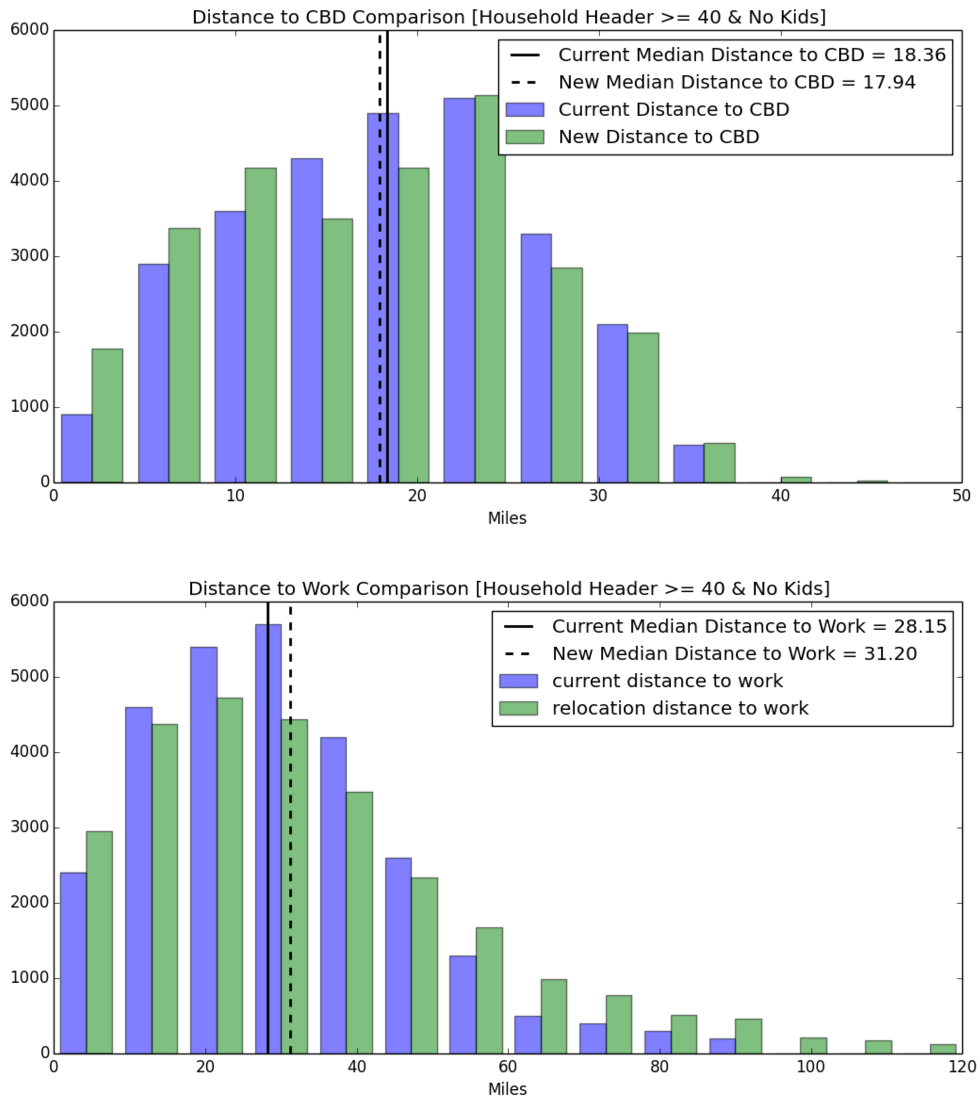


Figure 14: New Location Choices for Households Above 40 & No Kids

Elder households with kids are also moving slightly closer to the CBD. The median distance to CBD declines from 19.56 to 18.28 miles. Zones that are less than 20 miles to urban core become more attractive to these households. These commuters can afford more expensive properties with better accessibility and school quality due to the significant reduction in commute transportation costs. The selected properties in SAV scenario tends to be more expensive, as the price income ratio of selected properties increases from 4.79 to 4.85. Compared with elder households without kids, this type of household is willing to move further away from their working places, as the median distance to work increases by approximately 6 (20.9%) miles in the SAV scenario.

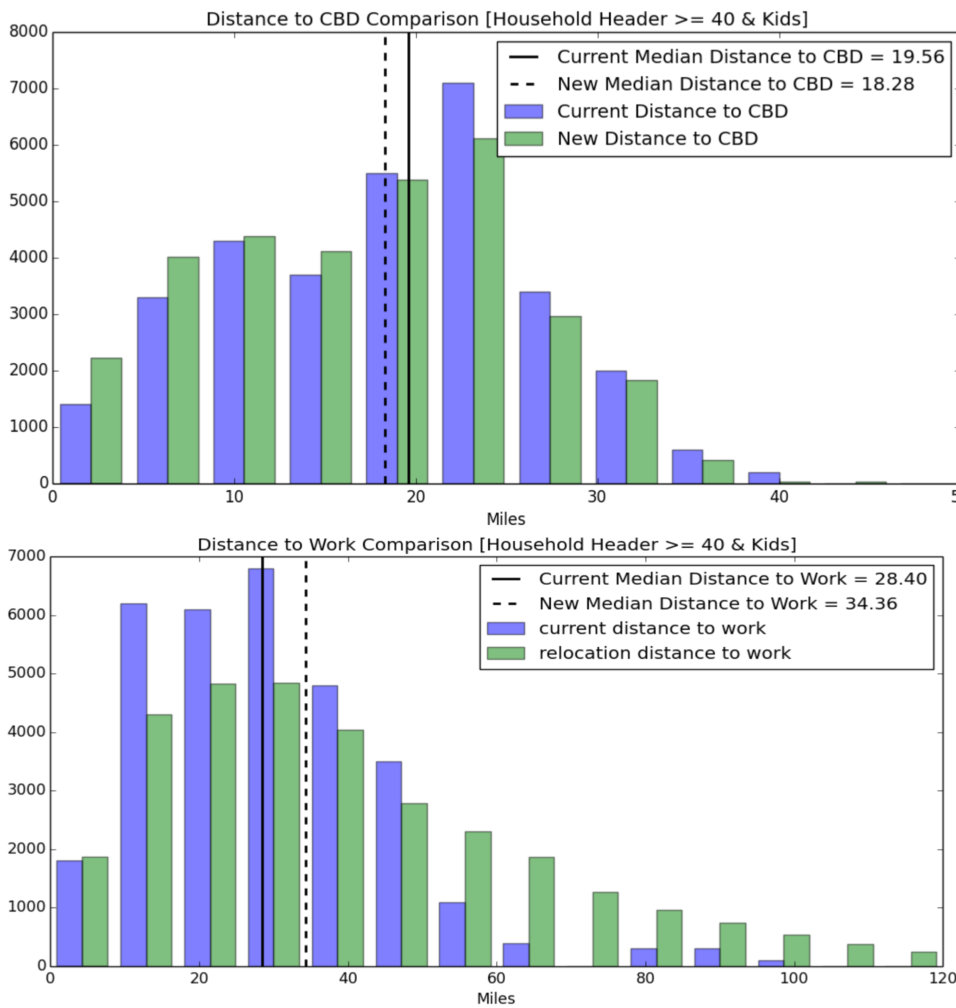


Figure 15: New Location Choices for Households above 40 & Kids

In summary, the results suggest that all market segments are going to be less attached to their working places. The properties with preferred structural characteristics, school districts and neighborhoods features will become more appealing to home buyers. Therefore, the SAV induced reduction in transportation costs provides more freedom for home buyers in terms of where they may live in the region. Meanwhile, the results also indicate a significant increase in the commute VMT, as the median commute distance per commuter increases for all market segments, ranging from 11% to 23%. Despite whether VMT generation for other trip purposes will decrease remains unclear, attention should be paid to develop travel demand management policies to curb commute VMT in the SAV scenario.

5.3 Model Validation and Verification

Multiple elasticity tests are conducted to determine how the model assumptions will affect the final results. First, SAV costs ranging from $0.13 to $0.50 per mile are examined to determine the elasticity of residential location choice to SAV fare. The results, as tabulated in Table 6, indicate the distance to office is negatively associated with the SAV fare, as workers will move closer to office locations with the increase in SAV fare. Meanwhile, households younger than 40 without kids are more sensitive to SAV costs compared with other market segments, given the largest reduction rate in distance to work per one unit of increase in SAV fare. This may attribute to the fact that the income level for young households without kids is comparative lower than the other households.

Table 6: Median Distance to Office per Worker by SAV fares (Miles)

	BAU	SAV - ¢15/mile	SAV - ¢30/mile	SAV - ¢50/mile
Households < 40 & No Kids	28.09	36.58	34.67	32.33
Households < 40 & Kids	29.48	33.80	32.62	30.88
Households >= 40 & No Kids	28.15	32.16	31.20	29.84
Households >=40 & Kids	28.40	34.80	34.36	33.55

The median distance to CBD, however, is not linearly associated with the change in SAV fare. For younger households, the higher the SAV fare the closer they are going to locate to CBD area to save commute costs. While for elder households, the distance to CBD is positively associated with SAV fare cost. The higher the SAV costs, the further the elder households are going to locate from CBD area. Such result is quite reasonable as, if the SAVs are as expensive as the current privately owned vehicle, there would be almost no significant deviations in the distribution of distance to CBD.

Table 7: median Distance to CBD by SAV fares (Miles)

	BAU	SAV - ¢15/mile	SAV - ¢30/mile	SAV - ¢50/mile
Households < 40 & No Kids	16.71	18.93	17.85	16.96
Households < 40 & Kids	20.70	23.55	23.08	22.09
Households >= 40 & No Kids	18.36	17.70	17.94	18.13
Households >=40 & Kids	19.56	17.89	18.28	18.98

Second, the assumption that in-vehicle-time (IVT) costs will be zero in the SAV scenario is relaxed and different portion of IVT costs are charged, ranging from 10% to 50%. The SAV fare costs are fixed at ¢30/mile. The outputs, as shown in Table 6 and 7, suggest that both distance to office and distance to CBD are quite sensitive to the charged portion of IVTT costs. Additionally, compared with changes with respect to SAV fare costs, the perceived IVTT costs tend to have a larger influence in residential location choices, as it occupies a larger amount of commute transportation costs.

Table 8: Median Distance to Office per Worker by IVTT costs (Miles)

	BAU	0%-IVT	10%-IVT	25%-IVT	50%-IVT
Households < 40 & No Kids	28.09	34.67	33.81	32.49	30.43
Households < 40 & Kids	29.48	32.62	31.83	31.27	29.72
Households >= 40 & No Kids	28.15	31.20	29.42	28.96	28.36
Households >=40 & Kids	28.40	34.36	33.31	31.75	28.97

Table 9：Median Distance to CBD by IVTT costs (Miles)

	BAU	0%-IVT	10%-IVT	25%-IVT	50%-IVT
Households < 40 & No Kids	16.71	17.85	17.33	17.10	16.99
Households < 40 & Kids	20.70	23.08	22.79	22.19	21.07
Households >= 40 & No Kids	18.36	17.94	17.98	18.09	18.23
Households >=40 & Kids	19.56	18.28	18.61	18.98	19.38

The elasticity tests partially verify the design of the model, as the tests tend to move towards the expected direction given changes in model assumptions and model parameters. Moreover, the test results also indicate the assumptions of SAV fare costs and perceived IVTT costs will only affect the magnitude of the moving trend and will not change the direction of changes in residential location choices.

5.4 Conclusions

In this chapter, the discrete-event agent-based SAV simulation model is joint with the residential location choice model to examine potential changes in residential land uses in the era of SAVs. The results suggest that most of the households are likely to move away from their working places and relocate to neighborhoods with more appealing property characteristics, socio-economic environment, and education resources. Therefore, the SAVs will provide more freedom in location choices for homebuyers. However, the model outputs also reveal an increase in commute VMT generation across all market segments. This may result in more congestions, commute energy consumption and air pollutants emissions. Policy makers may reduce such negative externality using commute travel demand management tools, including encouraging the use of transit and carpooling services. Meanwhile, it remains unclear whether the VMT generation for other trip purposes will increase or not, which deserves further explorations.

The model outputs also suggest that SAVs, to some extent, can help curb urban sprawl. First, SAVs can make compact development more appealing by offering more accessible mobility service with less average waiting time in densely developed neighborhoods. The elder generations are willing to move slightly closer to CBD area to avoid large waiting time costs in suburban areas. Despite the younger generations are fleet away from downtown area, the majority of this market segment still prefer to locate within the 25-mile network buffer to CBD area.

Some model limitations merit future modeling efforts. First, SAV is the only modelled travel mode in this model, mode choice between SAV and privately owned AV is not considered. Different model choice can significant change in the commute transportation costs, which may reverse the trends in residential location choices. Second, the trip assignment model is not included in this study. Therefore, it is assumed that congestion level will be the same as business as usual. However, SAV system tends to generate a larger amount of VMT, due to longer commuting distance and vehicle relocation process. To obtain more robust transportation costs in the era of SAVs, trip assignments module should be included in the model. Finally, the model assumes that residential location preferences, i.e., the coefficients, will not change over time, which is a quite strong assumption. More scenarios analysis can be conducted to explore residential location choices given changes in preferences.

CHAPTER 6. SAV AND EMPLOYMENT AGGLOMERATION

This chapter describes the methodology and data used to examine the variations in employment location choices after the introduction of SAVs. The preferences for firm locations are analyzed across industry sectors. The model simplifications and assumptions are verified using a series of elasticity tests. The results are also validated by comparing the distribution of firms from the 2015 Business as Usual (BAU) model outputs and the 2015 observed data. The last section of this chapter summarizes the primary findings in the changes of agglomeration and localizations patterns, planning policy implications, model limitations, and future directions.

6.1 Model Implementation

This study uses a three-step model framework to examine the choices of employment location in the SAV scenario. The first and second steps are similar to the methods used in the residential location choice models. First, employment location choice models are estimated to reveal the existing preferences for firm location by industry sectors using the MNL model. The considered explanatory variables include economy agglomeration and localization factors, access to local and regional human capitals, location accessibility, available rentable spaces. Second, in the era of SAVs, the accessibility to human capital and available commercial square feet are updated to reflect the reductions in commute costs and parking spaces brought by SAVs. Different from the residential location choice models, the firm relocation choices are simulated using agent-based simulation model, instead of the Monte Carlo simulation method.

6.1.1 *Step 1: Employment Location Choice Model Implementation*

6.1.1.1 Dependent Variables

2010 and 2015 ESRI business data, with geocoded firm locations, are used to develop employment location choice models by industrial sector. There is a total of 164,494 and 204,906 businesses in 2010 and 2015 dataset correspondingly. The datasets contain business names, business types, longitudinal firm locations, and the number of employees. In the 2015 ESRI data, approximately 92,767 firms locate on residential parcel data, indicating that the business is home-based. These home-based businesses are quite small, with only one or two employees on average. In this study, small home-based businesses (i.e. business size smaller than three) are filtered out, given that they are most likely to be self-employed businesses and may have dramatically different factors to consider regarding the location to start businesses. Finally, firms that started after 2010 or relocated between 2010 and 2015 are considered as firms who made location choices during the 5-year time window and are included in the Multinomial Logit Model. 70,086 firms or 563,129 jobs are used to estimate the final model.

All businesses are divided into eight industrial sectors based on Standard Industrial Classification (SIC) code to develop models correspondingly. Separate models are estimated for each sector, as most empirical employment location choice models suggest that firms from different sectors inherit significantly different location preferences (Waddell & Ulfarsson, 2003). Table 10 presents the classification of industry sectors based on the SIC code and the employment count.

Table 10: Number of New or Relocated Business by Industry Sectors

Industry Sectors	2-Digit SIC Code	Number of Jobs	Count of Firms	Average Size
Construction	15-17	13,258	1,224	10.8
Manufacturing	20 - 39	24,551	1,705	14.4
TCU	40 - 49	34,555	3,237	10.7
Wholesale	50 - 51	15,326	2,441	6.3
Retail	52 - 58	20,9483	7,085	29.6
FIRE	60-67	43,815	3,188	13.7
Services	70-89	191,357	17,055	11.2
Public	91 – 99	30,784	2,272	13.5
Total		**563,129**	**70,086**	**14.7**

The employment location choice models are developed at the TAZ level, rather than the parcel or building level, because there is no sufficient data with respect to each commercial building to develop disaggregated firm location choice model. For each business in the final dataset, nine alternative TAZs with corresponding commercial or industrial land uses are randomly selected. Together with the chosen one, ten alternatives are included in the model. The number of alternatives is smaller than that in the residential location choice model due to the significantly larger sample size.

6.1.1.2 Independent Variables

Based on both the theoretical and empirical literature, factors that may influence firm location choice include agglomeration economy/diseconomy, special indices and size of the firms, accessibility to human capital, fiscal condition of local government, transportation infrastructure accessibility, built environment characteristics, and other county-level policy factors. Table 11 tabulates a summary of all the considered independent variables in firm location choice models.

Table 11: Summary of Independent Variables in Employment Location Choice Model

Variable Type	Variables	Min	Max	Average	Std. Dev.	Data Source
Agglomeration economy /diseconomy	# Jobs in Sector 1 – Manufacture	0	7551	89.78	334.49	ESRI 2010
	# Jobs in Sector 2 – Construction	0	4183	67.03	155.19	ESRI 2010
	# Jobs in Sector 3 – TCU	0	6447	83.65	338.16	ESRI 2010
	# Jobs in Sector 4 – Wholesale	0	3004	68.80	213.47	ESRI 2010
	# Jobs in Sector 5 – Retail	0	4969	114.57	311.84	ESRI 2010
	# Jobs in Sector 6 – FIRE	0	6116	332.36	538.01	ESRI 2010
	# Jobs in Sector 7 – Services	0	23978	591.37	1227.98	ESRI 2010
	# Jobs in Sector 8 – Public	0	12500	95.33	516.15	ESRI 2010
	Job Density (per Acres)	0	963.12	6.31	35.28	ESRI 2010
	Average Employment Size	0	171.35	10.69	12.34	ESRI 2010
Human Capital/ Market Size	Access to Population with Bachelors	0	44.47	1.96	3.79	Created by Author
	Access to Population with High School	0	18.08	1.87	2.61	Created by Author
	Access to Population without High School	0	5.74	0.49	0.79	Created by Author
	Access to Labor Pool	0	57.80	3.76	6.23	Created by Author
	Rate of Unemployment	0	0.56	0.10	0.06	Census Bureau
Transportation Infrastructure	Distance to Expressway Exit (meters)	203.8	91045.9	13964.6	12730.4	Created by Author
	Distance to Highway (meters)	1.0	20980.4	4083.6	3330.5	Created by Author
	Distance to Airport (miles)	0.43	32.57	12.14	5.21	Created by Author
Built Environment	Commercial/Industrial Land Density	2.7	113683.3	2498.8	6791.8	Costar
	Population Density (2010)	0	60.23	3.67	3.55	Census Bureau
	Entropy (2010)	0.04	0.96	0.63	0.19	Created by Author
	Walkability (Walkscore)	0	96.00	18.38	21.66	Walkscore API
	Percent of Four-way Intersection	0	1.00	0.12	0.13	Created by Author
	Density of Four-way Intersection (per Km^2)	0	465.50	13.40	29.20	Created by Author
County Specific	Location Quotient (TAZ level)	0	139.64	1.67	3.54	Created by Author
	Property Tax Rate	0.63	1.37	1.04	0.22	Count Website
	Dummies for each County	NA	NA	NA	NA	Created by Author

Theories regarding agglomeration and localization economy suggest that firms can harvest benefits by locating near each other to share raw materials, skilled labor pools, markets, and infrastructures (Marshall, 2009). While theory of scale diseconomy indicates that the negative externalities stemming from the high density may prevent firms from agglomerating. The negative effects including congestion, server competition, and an insufficient amount of infrastructures. The variables used in this study includes TAZ level population density, firm density, change of population from 2010 to 2015, the number of firms and employees by industry sectors. Given the theory of agglomeration economy and diseconomy, the relationship of firm location choice is not linearly correlated with the density related independent variables (Bhat, Paleti, & Singh, 2014). Therefore, squared terms of these variables are also considered to reflect the phenomenon of diseconomy when the density becomes too high. The population related variables are calculated using 2010 and 2015 census or American Community Survey (ACS) data. The firm related variables are generated based on ESRI's 2010 and 2015 business data.

The Location Quotient (LQ) index is calculated by County to measure the specialization effects. The LQ is defined as the percentage of businesses from a certain industry sector for each county divided by the national percentage of the businesses in the same sector. The index is calculated using the formula below:

$$LQ_{i,j} = \frac{B_{i,j}/TotB_j}{B_{i,nation}/TotB_{nation}} \tag{35}$$

Where,

$LQ_{i,j}$ denotes LQ for industry sector i in County j;

$B_{i,j}$ denotes total number of businesses in industry sector i in County j;

$TotB_j$ denotes total number of businesses in County j;

$B_{i,nation}$ denotes total number of businesses in industry sector i in the nation;

$TotB_{nation}$ denotes total number of businesses in the nation.

LQ index specifically captures the effect of localization economy. A county may have low agglomeration economy while a high localization economy if the proportion of certain industry sector is significantly higher than the national average. Based on the theory of localization economy, firms from the same sector may decide to collocate to have higher access to specialized human capital and market.

Businesses need human capital to implement production and other revenue generating activities. Thus, the accessibility to skilled labor plays an important role in the choice of firm location. In this study, the accessibilities to the population by different level of education attainment are used to measure TAZ level access to human capital. The variables are calculated based on the subsequent formula:

$$HC_{edu,i} = \sum_{j=1}^{1593} pop_{edu,j} * e^{-TC_{ij}} \tag{36}$$

Where,

$HC_{edu,i}$ denotes the accessibility to human capital with education attainment (including below high school, high school and above bachelor), edu, in TAZ i;

$pop_{edu,j}$ is the total population with education attainment edu in TAZ j;

TC_{ij} indicates the total transportation costs between TAZ pair i and j.

Similar to the measurement used in the residential location choice models, the transportation impendence cost is a combination of both travel time costs and vehicle operation costs, as specified in the equation below.

$$TC_{ij} = time\ cost_{ij} + vehicle\ cost_{ij} \tag{37}$$

Currently, the time costs are associated with travel time and average hourly salary by industrial sector, obtained from the Bureau of Labor Statistics. The vehicle costs are estimated by multiplying the travel distance by the average vehicle costs per mile. The mile based vehicle cost is the weighted average costs estimated based on vehicle composition obtained from the 2010 local travel survey and 2016 AAA's vehicle cost report.

$$time\ cost_{ij} = IVTT_{ij} * average\ salary \tag{38}$$

$$vechiel\ cost_{ij} = dist_{ij} * average\ vehicle\ cost\ per\ mile \tag{39}$$

Fiscal conditions are also considered in the location choice model. Variables, such as county-level government expenditures and property tax are collected and calculated. The hypothesis is that government expenditures reflect county level investment in principal infrastructures to support economic activities. Prior studies suggest property tax can influence firm location choice via the supply of rentable spaces (Guimaraes, Figueiredo, & Woodward, 2004; Jofre-Monseny & Solé-Ollé, 2010).

Transportation infrastructure and built environment features also affect firm location choices (Bhat et al., 2014). Variables such as adjacency to various types of transportation infrastructures, including states expressways, highways, and airports, are examined in different models. Additionally, built environment features, such as developable land, walkability (using Walkscore), and percent of four-way and three-way intersections and cul-de-sacs, are also tested to determine whether TAZs with better infrastructure accessibility and more densely developed built environment are more appealing to firms in Atlanta metropolitan area.

Finally, other observable county level variables are included in the location choice model by introducing county binary variables. The coefficients of these dummy variables will capture the mean effect of unobserved county factors in firm location choices.

6.1.2 Step 2: Independent Variables Updates in the Era of SAV

The SAV model results with similar simulation settings as described in Section 5.1.2 are used to update two independent variables: 1) human capital accessibility variables, and 2) available rentable commercial and industrial spaces. The human capital accessibility will be improved significantly, due to the reduction in commute costs introduced by SAVs. The time costs, instead of being a linear function of IVTT, will be a linear function of OVTT costs at both ends of the trip. Furthermore, the average vehicle cost per mile will be replaced by SAV cost per mile, which ranges from 13 – 50 cents/mile. The updated equations for calculating human capital accessibility in the time of SAVs are shown as below:

$$HC_{edu,i} = \sum_{j=1}^{1593} pop_{edu,j} * e^{-TC'_{ij}} \tag{40}$$

$$TC'_{ij} = time\ cost'_{ij} + vehicle\ cost'_{ij} \tag{41}$$

$$time\ cost'_{ij} = \left(wait\ time_i + wait\ time_j\right) * average\ job\ salary \tag{42}$$

$$vechiel\ cost'_{ij} = dist_{ij} * SAV\ cost\ per\ mile \tag{43}$$

Additionally, SAV will lead to a reduction in urban parking spaces, which can be transformed into rentable commercial and industrial spaces. The most recent Atlanta parking inventory report indicates the average area of parking space in Atlanta is approximately 300 square feet (CAP, 2014). Therefore, the available square feet can be estimated as follow:

$$SF'_i = SF_i + Parking\ Reduction_i * 300 \tag{44}$$

In this study, elasticity tests with different parking space reduction rates, ranging from 25% to 90%, are conducted. The parking space reduction rate depends heavily on the market penetration of SAV.

6.1.3 Step 3: Employment Relocation Model Implementation

This work implements employment relocation model using the employment transition and employment relocation models in UrbanSim. The employment transition model in UrbanSim first generates new firms based on regional employment control totals across industry sectors from ARC. The employment relocation model then select a random sample of existing firms to relocate in the region, based on the average relocation rates by industry sectors. The relocation rate is calculated using ESRI 2011 and 2015 data, and the results are tabulated in Table 12. UrbanSim relocation choice model then allocates both the new and relocating firms into TAZs via Monte Carlo simulation method. The probability of selecting TAZ for relocation is computed using the estimated employment location choice model, i.e., TAZs with higher utility based on the employment location choice model are more likely to be chosen as the final relocation destinations.

Table 12: Annual Relocation Rate by Industry Sector

Industry Sector	Relocated Jobs (2010-2015)	Total Jobs	Annual Relocation Rate
Construction	13,258	95,302	2.8%
Manufacture	24,551	137,726	3.6%
TCU	34,555	105,843	6.5%
Wholesale	15,326	105,431	2.9%
Retail	209,483	426,851	9.8%
FIRE	43,815	154,192	5.7%
Services	191,357	825,865	4.6%
Public	30,784	155,144	4.0%
Total	**563,129**	**2,006,354**	**5.6%**

6.2 Model Results

6.2.1 Existing Firm Location Preferences

The results of firm location choice models by industry sectors are tabulated in Table 13. The non-significant variables are excluded in the final models. Similar to the residential location choice model, no alternative specific constants are introduced in the model. Additionally, there is also no base alternative in the estimated models. Therefore, the estimated coefficients can be directly interpreted with respect to the direction of change in the utility and can also be compared with other coefficients across models. Unstandardized independent variables are used in the models. This is because the variations in standardized

Table 13: Employment Location Choice Model Results by Industry Sectors

Types	Variables	**Manufac-turing** Estimation [Beta] (t-stats)	**Construc-tion** Estimation [Beta] (t-stats)	**TCU** Estimation [Beta] (t-stats)	**Wholesale** Estimation [Beta] (t-stats)	**Retail** Estimation [Beta] (t-stats)	**FIRE** Estimation [Beta] (t-stats)	**Services** Estimation [Beta] (t-stats)	**Public** Estimation [Beta] (t-stats)
Agglomeration Economy / Diseconomy	Sector specific job #	0.00725 [2.674] (75.25)	0.00313 [0.458] (132.3)	0.00259 [0.876] (118.95)	0.00567 [1.210] (117.17)	0.0024 [0.748] (166.92)	0.00189 [0.589] (75.27)	0.000217 [0.266] (57.21)	0.00112 [0.578] (105.79)
	Sector specific job # (Squared)	-3E-6 [-4.207] (-48.93)	-5E-7 [-0.220] (-102.35)	-3E-7 [-0.470] (-76.77)	-2E-6 [-0.200] (-52.52)	-5E-7 [-1.010] (-110.07)	-3E-7 [-0.300] (-52.59)	-7E-9 [-0.130] (-30.99)	-7E-8 [-0.310] (-70.85)
	# Jobs in Sector 1 – Manufacture	N/A	0.000951 [0.318] (21.72)	0.000139 [0.046] (2.89)	-	-	-	-0.000119 [--0.040] (-5.30)	-0.000488 [-0.163] (-11.23)
	# Jobs in Sector 2 – Construction	-	N/A	0.000164 [0.025] (6.91)	0.000244 [0.038] (20.2)	-0.000163 [-0.025] (-17.24)	-	-0.00007 [-0.011] (-7.69)	-
	# Jobs in Sector 3 – TCU	0.000166 [0.056] (5.61)	0.000313 [0.106] (132.3)	N/A	-	-0.00092 [-0.031] (-12.10)	-0.000154 [-0.052] (-9.09)	-0.000279 [-0.094] (-24.25)	-
	# Jobs in Sector 4 – Wholesale	0.000269 [0.057] (5.29)	0.000168 [0.036] (8.04)	0.000556 [0.119] (16.88)	N/A	-	-0.000434 [-0.093] (-16.33)	-0.000393 [-0.084] (-24.49)	0.000265 [0.057] (6.56)
	# Jobs in Sector 5 – Retail	-	-0.000092 [-0.029] (-5.94)	-	-	N/A	-	-0.000319 [-0.099] (-48.68)	-
	# Jobs in Sector 6 – FIRE	0.000149 [0.032] (5.59)	0.000312 [0.168] (12.55)	-	-0.000085 [-0.046] (-3.14)	0.000047 [0.015] (5.86)	N/A	-	0.00027 [0.084] (13.61)
	# Jobs in Sector 7 – Services	-	-0.000154 [-0.189] (-18.02)	-	-	-	0.000152 [0.188] (26.84)	N/A	-0.000041 [-0.050] (-6.11)
	# Jobs in Sector 8 – Public	-	-	-	-	-0.000201 [-0.104] (-22.27)	-0.000191 [-0.099] (-12.77)	-0.000136 [-0.070] (-26.68)	N/A

Types	Variables	**Manufac-turing** Estimation [Beta] (t-stats)	**Construc-tion** Estimation [Beta] (t-stats)	**TCU** Estimation [Beta] (t-stats)	**Wholesale** Estimation [Beta] (t-stats)	**Retail** Estimation [Beta] (t-stats)	**FIRE** Estimation [Beta] (t-stats)	**Services** Estimation [Beta] (t-stats)	**Public** Estimation [Beta] (t-stats)
	Log Job Density (per Acres)	0.0567 [0.049] (6.19)	0.131 [0.114] (12.98)	0.200 [0.173] (17.44)	0.0949 [0.083] (9.16)	0.127 [0.110] (30.12)	0.839 [0.727] (105.95)	0.960 [0.832] (249.57)	0.236 [0.205] (26.64)
Human Capital/ Market Size	Access to Population with Bachelors		-0.0587 [-0.223] (-8.35)	-0.0135 [-0.051] (-3.24)	-	-	0.0662 [0.251] (9.96)	-	-
	Access to Labor Pool	-	-	-	-	-	-	0.0314 [0.397] (11.54)	0.0139 [0.176] (9.87)
	Average Income (Synthesized)	-	-0.000027 [-0.958] (-16.94)	-0.000005 [-0.178] (-12.58)	-	-	-	-	-
Transportation Infrastructure	Distance to Expressway Exit (meters)	-	-	-	-0.000005 [-0.064] (-3.36)	- 0.000006 [-0.077] (-11.33)	-0.000004 [-0.051] (-3.28)	-0.000006 [-0.076] (-12.41)	-
	Distance to Highway (meters)	-0.00004 [-0.133] (-9.35)	-0.000035 [-0.117] (-9.26)	-0.000026 [-0.087] (-5.28)	-	-0.000021 [-0.070] (-11.45)	-0.000027 [-0.090] (-8.37)	-0.000021 [-0.070] (-12.95)	-0.000078 [-0.260] (-15.68)
Built Environment	Ln Commercial/ Industrial Land Density	-0.046 [-0.038] (-1.856)	-0.022 [-0.019] (-3.34)	-0.0555 [-0.047] (-6.96)	-0.0138 [-0.012] (-1.86)	-	0.0636 [0.053] (2.13)	0.0168 [0.014] (3.64)	0.104 [0.087] (16.57)
	Average Land Value (per SQFT)	-0.000019 [-0.064] (-34.03)	-0.000028 [-0.094] (-82.52)	-0.000031 [-0.104] (-93.26)	-	-	-	-	0.0000337 [0.011] (125.04)
	Ln Population Density (2010)	-0.246 [0.105] (-43.35)	-	-	-	0.158 [0.067] (29.56)	-	-	-
	Entropy (2010)	1.37 [0.274] (17.52)	2.62 [0.524] (34.67)	0.705 [0.141] (9.38)	1.63 [0.326] (20.04)	0.360 [0.072] (10.24)	-	0.199 [0.040] (7.040)	-

Types	Variables	**Manufac-turing** Estimation [Beta] (t-stats)	**Construc-tion** Estimation [Beta] (t-stats)	**TCU** Estimation [Beta] (t-stats)	**Wholesale** Estimation [Beta] (t-stats)	**Retail** Estimation [Beta] (t-stats)	**FIRE** Estimation [Beta] (t-stats)	**Services** Estimation [Beta] (t-stats)	**Public** Estimation [Beta] (t-stats)
County Specific	Clayton	-	0.469 [0.469] (2.308)	-	-	-	-	-	-
	Cobb	0.397 [0.397] (1.941)	0.833 [0.833] (5.243)	0.610 [0.610] (4.55)	0.499 [0.499] (3.344)	0.679 [0.679] (8.52)	0.584 [0.584] (3.591)	0.502 [0.502] (9.089)	0.291 [0.291] (2.054)
	Dekalb	-	0.608 [0.608] (3.513)	-	0.385 [0.385] (2.474)	0.371 [0.371] (4.482)	0.400 [0.400] (2.372)	0.280 [0.280] (4.715)	-
	Douglass	-	0.840 [0.840] (4.082)	-	-	-0.270 [-0.270] (-2.074)	0.658 [0.658] (3.120)	-	0.457 [0.457] (2.390)
	Fayette	0.530 [0.530] (1.738)	0.537 [0.537] (2.630)	0.345 [0.345] (1.782)	0.440 [0.440] (1.972)	-	-	0.202 [0.202] (2.539)	-
	Fulton	-	-	-	-	0.455 [0.455] (3.130)	0.308 [0.308] (1.891)	-	0.370 [0.370] (2.509)
	Gwinnett	-	-	-	-	-	-	-0.151 [-0.151] (-2.620)	-0.503 [-0.503] (-3.507)
	Henry	-	0.440 [0.440] (2.136)	-	-	-	-	-	-
	Rockdale	-0.944 [-0.944] (-2.942)	0.913 [0.913] (4.351)	-	-	-0.633 [-0.633] (-4.404)	-	-0.313 [-0.313] (-3.661)	-0.965 [-0.965] (-3.321)
Log Likelihood		-27798.5	-42933.8	-32528.5	-35088.5	-170008.1	-43591.7	-207553.3	-40273.3
MacFadden R^2		0.319	0.357	0.362	0.344	0.208	0.423	0.484	0.400
Sample Size		13,258	24,551	34,555	15,326	209,483	43,815	191,357	30,784

human capital access and SF density variables are quite small between SAV and BAU scenario, rendering it hard to determine the differences from the two examined scenarios.

The results tabulated in Table 13 are consistent with the existing theories regarding firm location choices. The agglomeration economy or diseconomy related variables, such as industry specific employment in the TAZ and squared version of the variables, are significant and with expected signs across all the models. The squared industry specific firm count variables have negative signs while industry specific employment counts have positive signs. This suggests that when the density is low, jobs agglomerate in TAZs with comparatively larger sector-specific employment. However, when the employment density in the TAZ reaches a certain threshold, the TAZ turns out to be less appealing to businesses to avoid fierce competitions. The model also suggests that firms generally prefer to agglomerate in TAZs with larger total employment density, as the signs for the estimated coefficients of total employment variables are positive and the estimations are significant across different sectors.

The results also support the localization economy theory, which suggests that jobs from different sectors agglomerate to achieve mutual benefits. Manufacture jobs tend to be positively associated with jobs in sectors, such as TCU, wholesale, and FIRE. Construction sector jobs are more likely to coexist with jobs from manufacture, TCU, wholesale, and FIRE. TCU employment agglomerates with manufacture, construction, and wholesale businesses and is not significantly correlated with retail, FIRE, service, nor Public jobs. Jobs in the Wholesale sector tend to locate in TAZs with more construction employment and less FIRE employment. Jobs in the retail sector are negatively associated with jobs from the construction, TCU, and Public sectors, however, are positively correlated with jobs from the FIRE sector. FIRE jobs coexist with employment in the service sector and are negatively correlated with jobs from the TCU, wholesale, and Public sectors. It appears that services jobs are negatively associated with almost all types of jobs, except for FIRE jobs, which turns out to be not significant. Jobs in the public sector are negatively associated with the manufacture, wholesale, and services jobs when controlling all the other independent variables.

In short, the results for agglomeration economy or diseconomy variables suggest that there is an inverted U-shaped urbanization pattern for all industry sectors. Additionally, the urbanization economy is dominant in the region, as the estimations for job density all have positive signs and are significant. The localization economy, however, is not as dominant as the urbanization economy, as the correlations of jobs across sectors are sometimes non-significant or even negative. The localization economy, to some extent, relies heavily on the design of local zoning ordinance.

Human capital or market size variables are significant in models for several industry sectors. However, the signs for the estimated coefficients are not consistent. For instance, jobs in FIRE sector prefer to locate in TAZs with higher access to the population with bachelor or above education attainment. For Businesses in services and public sectors, TAZs with better access to the overall labor pool (i.e., population above 25) turn out to be more appealing. Meanwhile, construction and TCU sectors tend to locate in TAZs with less access to the population with higher education attainment and average income level. Manufacture jobs prefer TAZ with lower population density, due to the negative externality generated by the sector. Retail jobs are more likely to follow the market, reflected in the positive and significant estimation for population density variable. Both manufacture and retail jobs are more influenced by the market size at the TAZ level, rather than the regional level, as regional accessibilities related variables are not significant.

Transportation infrastructures variables including distance to highway and expressway exit are negatively correlated with TAZ utility, which is also consistent with the existing theories. Proximity to expressway exits is critical to location decision for jobs in the wholesale sector. Distance to highway turns out to be important for sectors such as manufacture, construction, TCU, and public. For jobs in retail, FIRE, and services sectors, estimations for both distances to expressway exits, and highway are negative and significant.

Built environment characteristics, such as entropy index and commercial/industrial land square feet density, average land value, and entropy index, are significant for the majority of sectors. Jobs in the manufacture, construction, TCU, and wholesale sectors prefer to locate in TAZ with lower commercial and industrial land density and lower average land value. While the estimations for the commercial and industrial square feet density are positive, ranging from 0.0168 to 0.104 for FIRE, services, and public sectors, indicating these jobs prefer to locate in TAZs with more intensive commercial and industrial activities. Further, Public sector prefers TAZs with higher average land value. This is because businesses in the public sector are more likely to obtain Tax exemptions from the government. Finally, most sectors prefer TAZs with higher land use diversity, as the estimated coefficients for entropy index are positive for almost all sectors, except for FIRE and public sectors.

Finally, some county specific dummy variables are significant in different models. Location quotient and tax rate variables are no longer significant after introducing county specific dummies into the models. Manufacture, construction, TCU, and wholesale jobs tend to locate in peripheral counties, such as Clayton, Douglas, Fayette, Henry, and Rockdale. Meanwhile, Retail, FIRE, Services, and public jobs prefer counties such as Cobb, DeKalb, and Fulton. The results also show that Cobb County is more attractive to almost all jobs across sectors, with positive and significant coefficients in all models.

In summary, the results show that: 1) Sectors, such as manufacturing, construction, TCU, and Wholesale, cannot afford the rent in the central region and therefore prefer to locate in TAZs that is further from the downtown area; 2) Sectors, such as FIRE, services, and public sectors choose to locate in inner city and carry out more intensive economic activities; 3) Retail sector relies heavily on the market size at the TAZ level and therefore tend to follow the distribution of population.

6.2.2 Variations in Independent Variables

In the SAV scenario, the accessibilities to different types of labor pool are updated using average waiting time outputs from the SAV simulation model, as shown in Figure 11, following formula 40-43. The results indicate on average the accessibilities to the population with bachelor or above degrees doubled in the region, due to the remarkable reduction in transportation costs. Meanwhile, the improvement is not evenly distributed, as shown in Figure 16, as the percent of improvement in the peripheral area is higher than the downtown area. This is because the current accessibility to human capital in the remote areas are quite low. However, despite the smaller percentage increase in downtown area, the increase in absolute magnitude peaks in compact areas (see Figure 16 right). Such change in accessibility is consistent with results in the Switzerland Study (Meyer, Becker, Bosch, Axhausen, 2017). Further, compared with the southern part of the region, the accessibility to bachelor increases more in the northern TAZs.

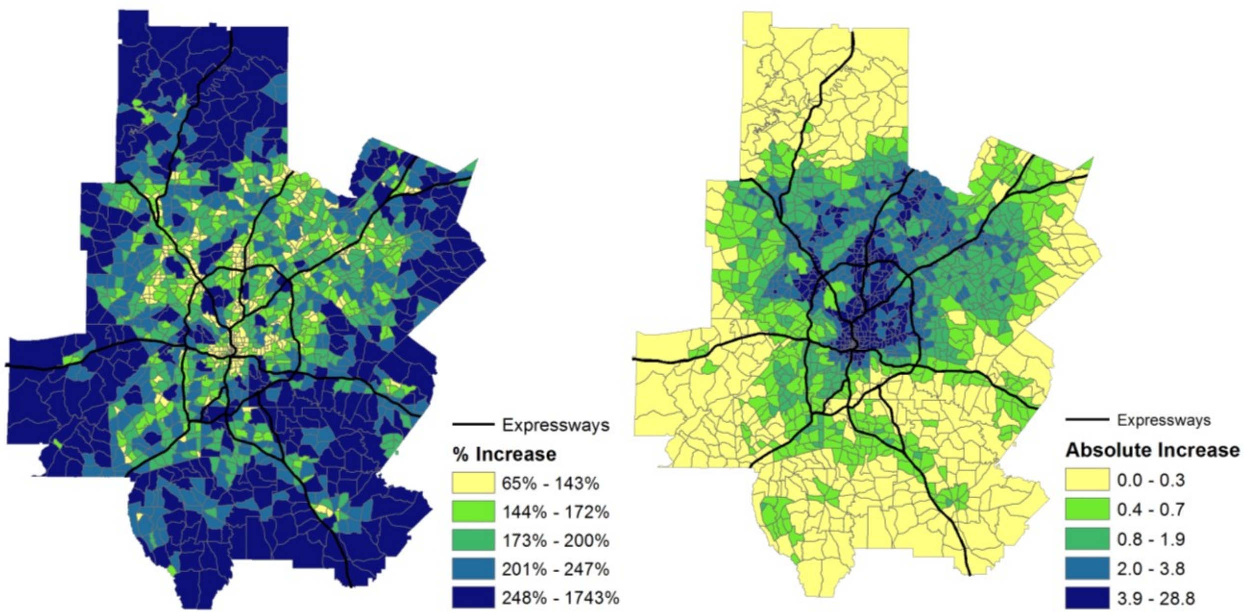


Figure 16: Change in Access to Population with Bachelor or Higher Education

In the SAV scenario, it is assumed that 90% of the existing parking spaces can be converted into the commercial or industrial use and result in higher density in TAZs. The parking spaces for current commercial or industrial properties are obtained from the Costar dataset. The variable is then updated using Formula 42 and results are plotted in Figure 17. On average, the commercial and industrial square feet density increase by 10.7%, assuming a 90% parking land conversion rate. The density increases most significantly in Central areas and TAZs adjacent to highways and expressways, where the existing parking land density is comparatively higher. Additionally, similar to changes in access to human capital, the absolute increase in commercial and industrial land density is the highest in urban core areas.

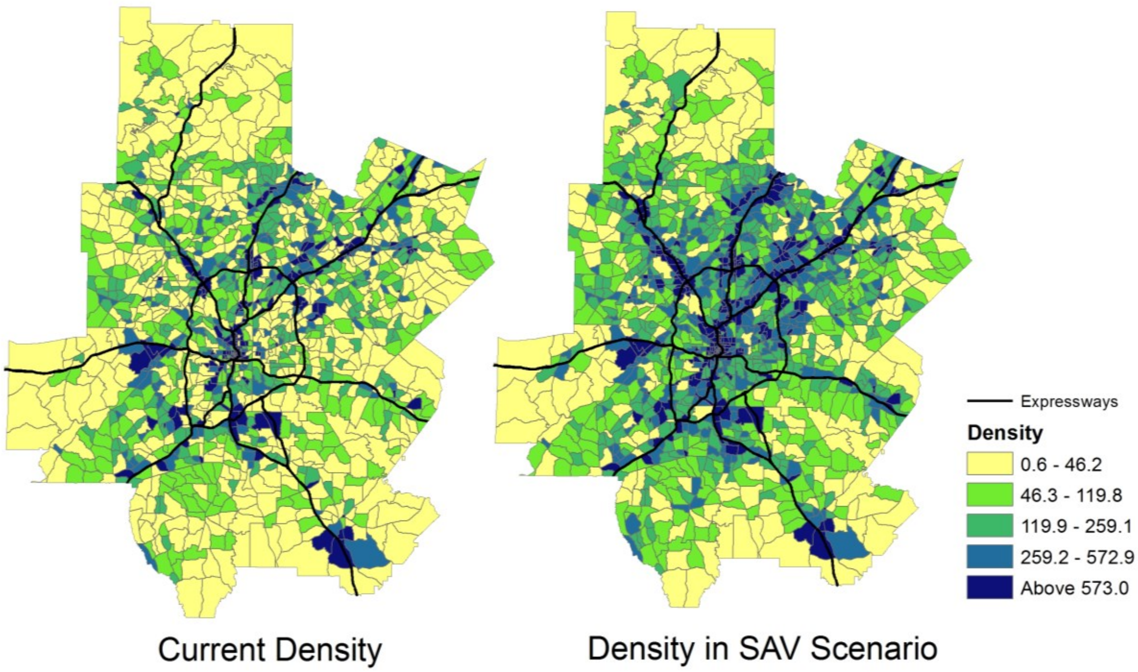


Figure 17: Changes in Commercial and Industrial Density

6.2.3 New Employment Agglomeration Patterns

Two scenarios of employment relocation choice model are implemented in UrbanSim. The SAV scenario is implemented with updated access to human capitals and commercial and industrial land density. The BAU scenario is implemented using the current TAZ level variables. For both scenarios, the relocation of employment is simulated for five years iteratively (i.e., from the base year 2010 to the target year 2015). The output 2015 employment results in incorporated cities are then aggregated by different existing land use intensities, such as downtown, inner city, inner ring suburban and outer ring suburban areas. The classification is made based on the built year of structures (Lee, 2005) [1]. The classification of these areas are shown in Figure 18.

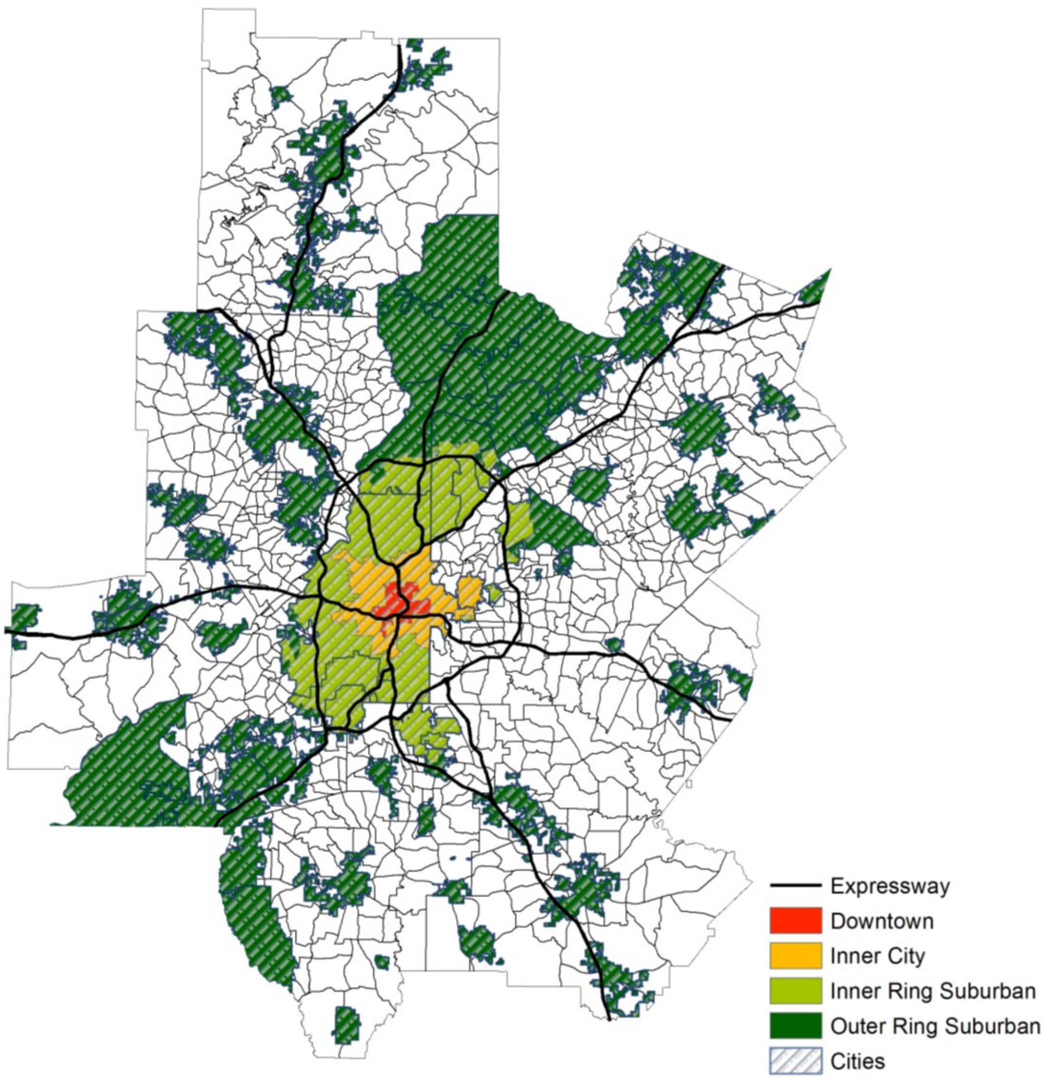


Figure 18: Cities Classification by Land Use Intensity

[1] Lee (2005) classified Atlanta metropolitan area into downtown, inner city, inner ring suburban ,and outer ring suburban based on the dominance of built year of structures, density and dependency of automobiles. For instance, inner ring suburb refers to communities that are low density, single-family areas, which were typically developed between 1950 – 1969. The primary transportation access mode is automobile. More detailed classification can be found in Lee's dissertation Section 3.2.2 (pp. 80-94)

The results from the BAU and SAV scenarios by industry sectors are tabulated in Table 14. The results suggest that SAVs may exaggerate the current migration trend for commercial and industrial economic activities in the region. In the SAV scenario, sectors, such as construction, manufacture, TCU, and wholesale, are more likely to relocate to suburban areas, as the job density for these sectors decreases significantly in downtown and inner city areas. While the job density in the inner ring and outer ring suburban areas increases in the SAV scenario. Construction jobs are most likely to relocate in inner ring suburban areas. Manufacturing, TCU, and wholesale job densities increase the most in cities located outer ring suburban areas.

Meanwhile, sectors such as FIRE, Service, and public are likely to concentrate more in cities in downtown and inner city areas. The job density in the downtown area increases by 11.8%, 1.4% and 3.1% for FIRE, service, and public sectors correspondingly in the SAV scenario. For these sectors, it appears that the densities of jobs reduce most significantly in the inner ring suburban areas, ranging from 5.9% to 7.8%.

Retail job density increases in cities in almost all types of urban areas. The inner city area is mostly likely to experience a significant increase in retail density. The increase rate is approximately 4.8%. The retail job density in the downtown area also increases by 0.8%. Meanwhile, unlike FIRE, service and public sectors, the job density for retail sector also increases slightly in inner ring suburban areas and outer ring suburban areas by 0.002% and 0.6% correspondingly. This is because retail sectors tend to follow the spatial distribution of the market.

Table 14: Job Density by Industry Sector across Scenarios

Industry Sectors	Scenarios	Downtown	Inner City	Inner Ring Suburban	Outer Ring Suburban
Construction	BAU	0.655	0.214	0.109	0.111
	SAV	0.576	0.180	0.120	0.115
	Change	-12.1%	-15.9%	9.8%	3.8%
Manufacture	BAU	0.597	0.190	0.115	0.103
	SAV	0.555	0.178	0.115	0.104
	Change	-6.9%	-6.0%	0.2%	1.0%
TCU	BAU	1.192	0.602	0.400	0.133
	SAV	0.983	0.546	0.402	0.139
	Change	-17.5%	-9.4%	0.5%	4.5%
Wholesale	BAU	0.490	0.193	0.143	0.110
	SAV	0.431	0.189	0.153	0.120
	Change	-12.0%	-1.8%	6.6%	8.3%
Retail	BAU	1.895	0.737	0.578	0.332
	SAV	1.910	0.773	0.578	0.334
	Change	0.8%	4.9%	0.0%	0.6%
FIRE	BAU	1.858	0.462	0.492	0.200
	SAV	2.077	0.462	0.454	0.195
	Change	11.8%	0.0%	-7.8%	-2.5%
Service	BAU	14.393	2.052	1.398	0.721
	SAV	14.591	2.067	1.316	0.702
	Change	1.4%	0.7%	-5.9%	-2.7%
Public	BAU	7.573	0.444	0.155	0.097
	SAV	7.810	0.445	0.143	0.091
	Change	3.1%	0.3%	-7.4%	-6.9%

The total employment density in different groups of cities is not changing significantly, as the percent changes in total job density in all areas are less than 0.1%. This indicates that although SAVs are likely to change the spatial distribution of jobs by industry sectors, the firms are not going to sprawl outside of the city, due to the agglomeration effects. However, it appears that SAV may further segregate different types of jobs in the region. For instance, Manufacture, Construction, TCU, and Wholesale jobs will migrate to cities with a lower hierarchy in the region. While, sectors such as FIRE, service, and public will become more dominant in the cities with higher hierarchy.

6.3 Model Validation and Verification

The model is validated by comparing the results from the BAU scenario with the 2015 ESRI observed business data. Spearman correlations are calculated by industry sectors, as shown in Figure 19. The results suggest that the model is robust as the BAU results are highly correlated with the observed employment distribution patterns in the TAZs by the year 2015. The correlations for Manufacture, Wholesale, and Services sectors are the lowest. However, even for these sectors, the correlations remain above 0.7. The correlation is the highest for the TCU sector, which is 0.84. The high correlations between the simulated BAU results and the observed ESRI 2015 results, to some extent, validate the model framework and the estimated coefficients in the employment location choice models. The differences between the BAU outcome and 2015 observed data can be attributed to the changes in location preferences over time and the missing control variables in the employment location choice models.

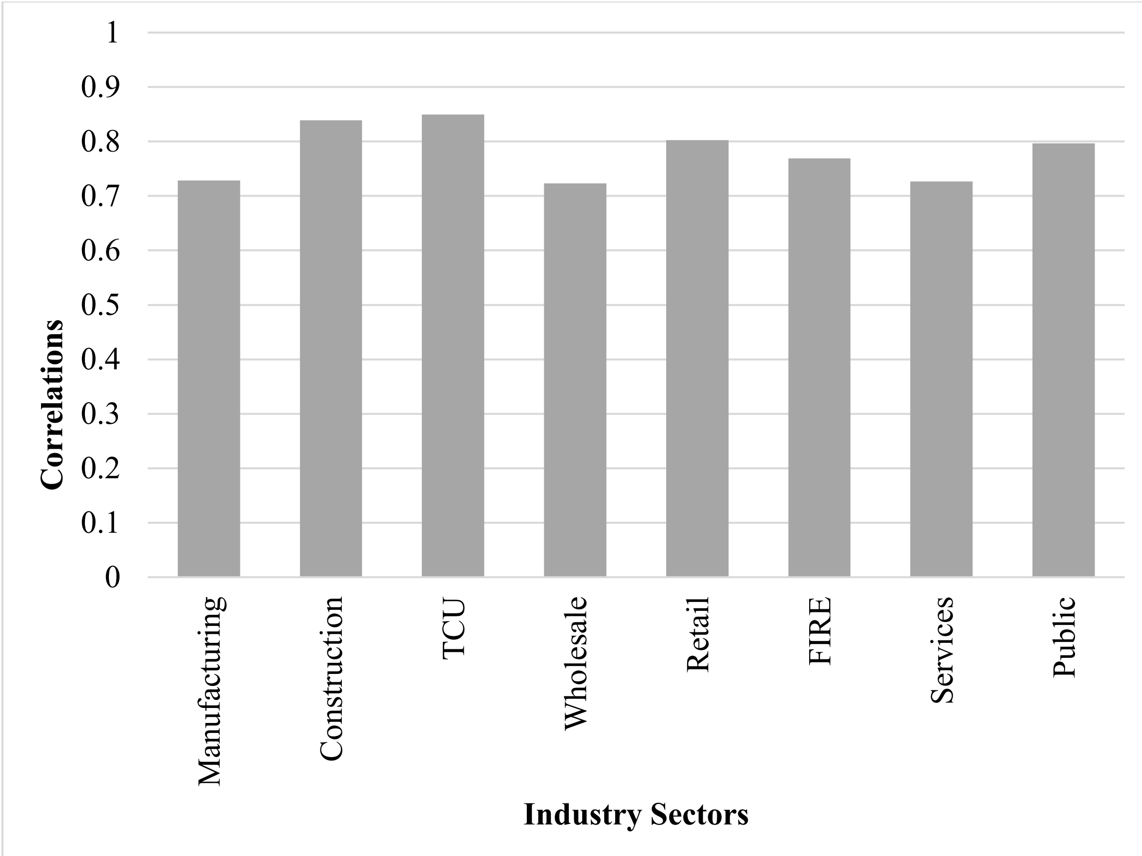


Figure 19: Correlations between BAU results and Observed 2015 ESRI Business Data

Additionally, the model is also verified by conducting a series of elasticity tests. First, various parking lots conversion rates, such as 25% and 50%, are examined and compared with the 90% conversion rate scenario. The results, as shown in Table 15, suggest that different parking conversion rate is not going to change the employment relocation trends across sectors, as the signs of differences between SAV and BAU employment densities are stable. Some sectors, such as retail, services, and wholesales are less sensitive to the variations of parking conversion rates, as the estimated coefficients for the commercial and industrial land density in models for these sectors are not significant or quite small in magnitude.

Additionally, for sectors that are sensitive to changes to parking conversion rate, the results show that the variations in model outputs are not linearly associated with the changes in parking conversion rate. For instance, the downtown employment density for construction sector decreases by 11.6% in the scenario where 25% parking are converted into commercial or industrial use. The reduction rate only increases to 14.2% when the parking conversion rate is doubled. Further, the reduction rate is merely 15.6% when the parking conversion rate rises to 90%. This is because the utility of location choices are associated with the log-transformed commercial and industrial land density. As a result, the changes in employment density diminishes when increasing the parking conversion rate from 50% to 90% than increasing the conversion rate from 25% to 50%.

Table 15: Changes in Employment Density (Compared with BAU results) by Different Parking Conversion Rates

Industry Sectors	Parking Conversion Rates	Downtown	Inner City	Inner Ring Suburban	Outer Ring Suburban
Construction	25% Conversion	-11.59%	-10.30%	7.16%	3.49%
	50% Conversion	-14.22%	-13.67%	10.09%	4.32%
	90% Conversion	-15.60%	-16.70%	10.53%	4.39%
Manufacture	25% Conversion	-2.92%	-2.29%	0.07%	0.32%
	50% Conversion	-5.28%	-4.84%	0.16%	0.83%
	90% Conversion	-6.90%	-6.00%	0.20%	1.00%
TCU	25% Conversion	-7.60%	-4.53%	0.21%	1.94%
	50% Conversion	-12.36%	-7.42%	0.36%	3.82%
	90% Conversion	-17.50%	-9.40%	0.50%	4.50%
Wholesale	25% Conversion	-10.26%	-1.65%	5.81%	6.96%
	50% Conversion	-11.36%	-1.58%	6.16%	7.97%
	90% Conversion	-12.00%	-1.80%	6.60%	8.30%
Retail	25% Conversion	0.84%	4.53%	0.00%	0.52%
	50% Conversion	0.69%	4.64%	0.00%	0.56%
	90% Conversion	0.80%	4.90%	0.00%	0.60%
FIRE	25% Conversion	4.13%	0.00%	-3.85%	-0.76%
	50% Conversion	9.30%	0.00%	-6.51%	-2.02%

Industry Sectors	Parking Conversion Rates	Downtown	Inner City	Inner Ring Suburban	Outer Ring Suburban
	90% Conversion	11.80%	0.00%	-7.80%	-2.50%
Service	25% Conversion	1.01%	0.52%	-4.19%	-1.94%
	50% Conversion	1.17%	0.63%	-5.21%	-2.31%
	90% Conversion	1.40%	0.70%	-5.90%	-2.70%
Public	25% Conversion	1.40%	0.10%	-3.38%	-3.22%
	50% Conversion	2.28%	0.22%	-6.31%	-5.80%
	90% Conversion	3.10%	0.30%	-7.40%	-6.90%

Finally, similar to the residential relocation choice models, the assumption that IVTT costs will be zero in the SAV scenario is also relaxed. Access to human capital is re-estimated with 25% and 50% charged IVTT to determine the impact of such assumption on the final outputs. The results of these elasticity tests are shown in Table 16. Some sectors, such has construction, TCU, FIRE, and public are very sensitive to the changes in the percent of charged IVTT costs. The results from these sectors suggest that the change in this assumption will not change the employment relocation trends in the region. However, the magnitudes of the changes are not linearly correlated with changes in the percent of charged IVTT. Meanwhile, the results for sectors, such as manufacture, wholesale, and retail, do not vary much across different elasticity tests, because the access to the population with bachelor or above degrees and the access to the entire labor pool are not significant for these sectors. The changes in these sectors are primarily induced by variations in other sectors that are sensitive to changes in human capital accessibility related variables.

Table 16: Changes in Employment Density (Compared with BAU results) by Different Percent of Charged IVTT

Industry Sectors	Charged Percent of IVTT	Downtown	Inner City	Inner Ring Suburban	Outer Ring Suburban
Construction	0% IVTT	-15.60%	-16.70%	10.53%	4.39%
	25% IVTT	-12.88%	-14.77%	7.75%	3.47%
	50% IVTT	-2.82%	-2.86%	1.98%	0.65%
Manufacture	0% IVTT	-6.90%	-6.00%	0.20%	1.00%
	25% IVTT	-6.41%	-5.11%	0.19%	0.81%
	50% IVTT	-5.79%	-4.64%	0.15%	0.82%
TCU	0% IVTT	-17.50%	-9.40%	0.50%	4.50%
	25% IVTT	-15.19%	-8.73%	0.47%	3.80%
	50% IVTT	-13.63%	-6.56%	0.26%	2.83%
Wholesale	0% IVTT	-12.00%	-1.80%	6.60%	8.30%
	25% IVTT	-11.83%	-1.45%	6.49%	8.16%
	50% IVTT	-10.03%	-1.45%	6.03%	6.17%
Retail	0% IVTT	0.80%	4.90%	0.00%	0.60%
	25% IVTT	0.70%	4.41%	0.02%	0.59%
	50% IVTT	0.62%	4.42%	0.01%	0.56%
FIRE	0% IVTT	11.80%	0.00%	-7.80%	-2.50%
	25% IVTT	9.27%	0.00%	-6.07%	-1.94%
	50% IVTT	1.94%	0.00%	-1.44%	-0.40%
Service	0% IVTT	1.40%	0.70%	-5.90%	-2.70%
	25% IVTT	1.16%	0.66%	-5.62%	-2.50%
	50% IVTT	0.70%	0.43%	-2.96%	-1.84%
Public	0% IVTT	3.10%	0.30%	-7.40%	-6.90%
	25% IVTT	2.63%	0.26%	-6.68%	-6.74%
	50% IVTT	1.77%	0.22%	-5.25%	-4.47%

In summary, the model validation results suggest that the developed employment location choice and relocation choice models are robust, given the high correlation between the results obtained in BAU scenario and the 2015 observed employment distribution pattern. Additionally, the elasticity tests also verify the design of the model, as the results change in the expected directions given changes in various model assumptions. Finally, the elasticity test results also indicate that the changes in access to human capital and commercial and industrial land density will not affect all industry sectors equally. For instance, the location choice in the retail sector is not sensitive to both variables. Firms in the manufacture and wholesale sectors are only sensitive to commercial and industrial land density.

6.4 Conclusions

The results suggest that different economic sectors will move in opposite directions in the SAV scenario. Secondary economic sectors, including Manufacture, construction, TCU, and wholesale sectors, are more likely to concentrate in cities in the lower hierarchy in the region. Meanwhile, tertiary sectors, such as FIRE, service, and public, are going to agglomerate more densely in cities in the higher hierarchy in the region. The density of retail employment will increase slightly in cities in different hierarchies, especially the ones in the inner city area. This is because retail sector follows the distribution of markets or population in the region more closely than other sectors. Nowadays, most large cities in the U.S. have already witnessed the deindustrialization phenomenon in the past decade, i.e., the decrease in the employment density of secondary sectors and the increase in the employment density of tertiary sectors. The current deindustrialization process is contributed primarily by the globalization phenomenon and robotic automation technologies. The results from this dissertation indicate the introduction of the SAVs will accelerate the existing deindustrialization trends in major U.S. cities.

The simulation results and elasticity tests discussed in this chapter offer insights on how land accessibility changes and parking land use redevelopment will influence spatial distributions of employment for different sectors in the era of SAV. However, the design of this simulation and its application can be improved in several ways. For instance, this model only considers the demand side of the location decision making; the supply side is not included in the model. The spatial distribution of new commercial property development will inevitably alter the location choices. Additionally, the equilibrium of bid and rent will also change with alterations in the supply of commercial land in the region. These components are not considered in the current simulation model. Similar to the residential location choice model, the employment location choice can also be more robust if multiple modes of accessibility are included in the land accessibility measurements. However, despite all these limitations, this model remains solid to explore potential changes in employment location choices in the SAV dominant scenarios.

CHAPTER 7. CONCLUSIONS AND FUTURE WORK

Among different business models of autonomous vehicles, shared autonomous vehicle (SAV), a driverless taxi system, is considered as the most promising and arguably most sustainable option as future mobility solution. The system is not only more affordable but also more environmentally friendly compared with the current conventional vehicles and private automated vehicles. The introduction of such travel mode will ultimately influence urban forms. However, to date, there remain research gaps regarding how SAVs may influence urban forms under various scenarios.

This dissertation addresses some critical questions regarding the impact of SAVs on urban forms, including 1) how will SAVs affect urban parking demand and parking land use, 2) how will SAVs influence residential location choices, and 3) how will SAVs affect employment agglomeration patterns in the region. Simulation based methodologies are used to address the research questions, as the SAV system is still under development. Based on existing agent-based SAV simulation studies, a discrete event based SAV simulation model is developed in Chapter 3. The model recreates virtually a scenario in which SAVs are assigned to fulfill the travel demand generated by residents. The spatial resolution of the simulation is the Traffic Analysis Zone (TAZ). The model first randomly generates trips based on the local Origin-Destination (OD) matrix from the four-step travel demand model. The departure times of trips follow the distribution obtained from the weighted local travel survey. The first-day simulation is used as a “warm-up” simulation to determine the fleet size and, therefore, is excluded in the final analysis. At the beginning of the first simulation day, the model randomly distributes vehicles in the region. Each time a client waits for more than 15 minutes, the model adds one more vehicle to the system to fulfill the demand immediately. The model always assigns the SAV with the least waiting time cost to serve incoming clients. The incoming clients will be put on a waiting list if all SAVs are occupied and will be prioritized for service once a vehicle becomes available again. After dropping off clients, the idling SAVs will be assigned either to relocate to underserved areas or to directly park. Such decision to continue relocating or to park is made based on the overall spatial distribution of available SAVs in the system. All the model results are collected after several simulation runs. Table 17 summarizes the SAV model settings to address different research questions.

Table 17: Model Settings for SAV Simulation Used in Chapter 4-6

Model Parameters	Q1: Parking Demand (Chap.4)	Q2: Residential Location Choice (Chap. 5)	Q3: Employment Location Choice (Chap. 6)
Study Area	Atlanta City	10- County Metro	10- County Metro
# of TAZs	208	1,593	1,593
MP	5%	100%	100%
# of Trips/Day	32,365	8,995,420	8,995,420
SAV Fleet Size	1000	367,160	367,160
DRS*	Included	Not included	Not included
LWS*	100%	-	-

* MP: Market Penetration; DRS: Dynamic Ride-sharing; LWS: Level of Willingness to Share

In Chapter 4, the designed SAV model is ran for 50 simulation-days to obtain future parking demand using data from the City of Atlanta. The results suggest that under a low market penetration level of 5%, the SAV system can still reduce proximately 4.5% of the parking land in both charged and free parking scenarios. One SAV holds the promise to eliminate approximately 20 parking spaces in the urban area. If the city is served exclusively by SAVs, then the system has the potential to reduce over 90% percent of existing parking spaces. SAVs reduce parking demand by increasing vehicle utilization rate and reducing vehicle ownership.

Additionally, the results from different parking price scenarios indicate that charged parking policies would be able to reduce both the total parking footprint of the system and the parking demand in the downtown area. However, there are negative externalities associated with the charged parking policy. For instance, in the expensive parking scenario, the parking demand of the SAV system tends to concentrate in low income neighborhoods, causing social equity issues. Further, SAVs generate significantly larger VMT footprint especially during vehicle relocation, picking up and parking processes, which leads to larger energy consumption and GHG emissions. Therefore, the parking price policies should be combined with other policies, such as environmental impact fee for unoccupied VMT, congestion fee, and GHG emission fees to curb negative environmental externalities of the system. Additionally, cities may also incorporate real-time parking price as a tool to balance the spatial distribution of SAVs to optimize the parking land use via improving the occupancy rates of the parking lots.

This dissertation also explores the impact of SAVs on residential land use by integrating the developed SAV model with the residential location choice model in Chapter 5. The results suggest that the SAV system is going to reduce the commute transportation costs by 77.1%. Given the existing preferences for residential location, different types of households harvest such cost reduction in different manners. Younger generation of households (i.e. below age of 40) are likely to move to communities with more appealing property characteristics, socio-economic environment, and education resources. These communities are typically further away from both urban cores and commuters' offices.

Senior households, on the other hand, will move closer to the downtown area, as these properties become more affordable after the decline in the commute costs. Like their younger peers, senior households are also going to move away from work places. In short, the technology provides households with more freedom in the choice of home location in the region. Meanwhile, the commute VMT generation is going to surge in the era of SAVs. Therefore, transportation and planning agencies should utilize travel demand management tools, including policies that encourage the use of transit and carpooling services, to curb VMT generation during peak hours. There is also an urgent need to integrate the SAV system with the transit system to achieve more sustainable development in the future.

The outputs from Chapter 5 also indicate that SAVs will not induce urban sprawl for the following reasons. First, urban cores become more attractive, as clients can expect to wait for shorter period in more intensively developed areas. In fact, results show senior households are willing to relocate closer to the CBD area to avoid the long waiting time in suburban areas. Second, although younger households are likely to relocate to communities slightly further from the downtown area, they are not going to sprawl into rural areas, due to a lack of high quality education resources and substantially longer average waiting time. Therefore, SAVs can help curb residential development in rural areas, by providing more convenient and affordable mobility services in compact areas.

In Chapter 6, the results of employment relocation choice model suggest that different industries will move in opposite directions in the SAV scenario. Secondary economic sectors, including manufacture, construction, TCU, and wholesale sectors will spill over into lower hierarchy cities in the region. Meanwhile, tertiary sectors, such as FIRE, service, and public, are going to agglomerate more densely in central cities in the region. The density of retail employment will increase slightly in all different cities, especially the ones in inner city areas. This is because retail sector follow the distribution of markets in the region more closely than other sectors. Currently, the density of secondary sectors in cities has already been decreasing, accompanied with the increase in tertiary sectors density in urban areas. Therefore, the results from Chapter 6 indicate the introduction of the SAVs will accelerate the deindustrialization phenomenon in cities.

There remain some limitations regarding the design and the implementation of the discrete event based SAV simulation model that merit future efforts. First, the model does not include trip assignment component. Despite the model uses different link level travel speed varying by time of the day, the travel speed is not sensitive to changes in induced empty VMT generated by the SAV system. At a high market penetrate level, the excessive VMT may change the level of service for some road segments significantly and is not captured in the current SAV simulation model. Second, the operation of the SAV system can be improved using optimization algorithms. For instance, the designed SAV model does not offer an optimized vehicle assignment algorithm to centralize the allocation of vehicles. Instead, clients are picked up at the first come first serve basis, which may not be the most efficient way to allocate available SAV resources in the system. Finally, the SAV system is the only modelled travel mode. Mode choice among SAV, privately owned AV, and integration of SAV or AV with transit system is not considered. However, the choice of different modes may change vehicle ownership and land accessibility significantly, which may influence the demand of parking, residential and employment location choices in the future. Therefore, these alternative scenarios for different business models of the operation of autonomous vehicles also deserve future research.

The SAV simulation model can also be improved in several specific ways to explore more parking policies related questions. For example, more research attention should be devoted to examine how the SAV system can be integrated as part of the sustainable urban growth by optimizing urban parking land use via smart parking pricing strategies. Furthermore, algorithm should be designed to better understand the tradeoffs between the VMT generation, congestions, and parking spaces reduction using a smart SAV system. Centralized optimization algorithm should be explored to help design the layout parking spaces that minimizes the negative environmental externalities.

The integration of SAV and residential location choice model can be more robust with the following improvements. First, more comprehensive research should be conducted to understand behavioral changes after the implementation of SAVs. Current model assumes that the people's travel behavior will mirror the current travel pattern, which may not be true in the future. Different trip generation and destination selection patterns may result in different choices in home location. In other words, the preferences in location choice may vary because of the changes in travel behavior and such hypothesis is not tested in this work. Instead, it is assumed that residential location preferences, i.e., the coefficients, will not vary over time. Therefore, more scenarios analysis can be conducted to explore residential location choices given variations in home location preferences.

Finally, the integrated SAV and employment location choice model can be improved by incorporating a land supply component into the existing framework. The implemented model in this work only considers the demand side of the firm location choice. However, the spatial distribution of new commercial property development (i.e., the supply side) also plays an important role in firm location choices. To model long-term changes in the employment agglomeration, it is necessary to incorporate a real-estate development component into the model and adopt a rent-bid equilibrium model framework.

REFERENCES

AAA. (2016). *Your Driving Cost: How much are you really paying to drive? (2016 Edition)*. Retrieved from http://exchange.aaa.com/wp-content/uploads/2016/04/2016-YDC-Brochure.pdf

ABI Research. (2013). Half of New Vehicles Shipping in North America to Have Driverless, Robotic Capabilities by 2032. Retrieved February 24, 2016, from https://abiresearch.com/press/half-of-new-vehicles-shipping-in-north-america-to-/

Agatz, N. A., Erera, A. L., Savelsbergh, M. W., & Wang, X. (2011). Dynamic ride-sharing: A simulation study in metro Atlanta. *Transportation Research Part B: Methodological*, *45*(9), 1450–1464.

Albright, J., Bell, A., Schneider, J., & Nyce, C. (2016). *Marketplace of change: Automobile insurance in the era of autonomous vehicles*. KPMG.

Alonso, W. (1964). Location and land use. Toward a general theory of land rent. *Location and Land Use. Toward a General Theory of Land Rent.*

Amey, A. (2011). A Proposed Methodology for Estimating Rideshare Viability within an Organization, applied to the MIT Community. In *TRB Annual Meeting Procediings* (pp. 1–16).

Baldacci, R., Maniezzo, V., & Mingozzi, A. (2004). An exact method for the car pooling problem based on lagrangean column generation. *Operations Research*, *52*(3), 422–439.

Barclays. (2016). *Disruptive Mobility: A Scenario for 2040*. Barclays Research.

Barth, M., Todd, M., & Xue, L. (2004). User-based vehicle relocation techniques for multiple-station shared-use vehicle systems.

Behdani, B. (2012). Evaluation of paradigms for modeling supply chains as complex socio-technical systems. In *Simulation Conference (WSC), Proceedings of the 2012 Winter* (pp. 1–15). IEEE.

Bhat, C. R., Paleti, R., & Singh, P. (2014). A spatial multivariate count model for firm location decisions. *Journal of Regional Science*, *54*(3), 462–502.

Birta, L. G., & Arbez, G. (2007). *Modelling and Simulation: Exploring Dynamic System Behaviour*. Springer.

Brailsford, S. C., & Hilton, N. A. (2001). A comparison of discrete event simulation and system dynamics for modelling health care systems.

Bridges, R. (2015). *Driverless Car Revolution: Buy Mobility, Not Metal*. Retrieved from Amerzon.com

Burns, L. D., Jordan, W. C., & Scarborough, B. A. (2013). Transforming personal mobility. *Earth Island Institute, Columbia University*.

CAP. (2014). *Parking Today: Downtown Atlanta Parking Assessment Existing Conditions*. Retrieved from http://www.atlantadowntown.com/_files/docs/existing-conditions-download.pdf

Chen, T. D. (2015). *Management of a shared, autonomous, electric vehicle fleet: vehicle choice, charging infrastructure & pricing strategies*.

Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). Operations of Shared Autonomous, Electric Vehicle Fleet: Two Implications of Vehilce and Charging Infrastructure Decisions.

Chester, M., Horvath, A., & Madanat, S. (2010). Parking infrastructure: energy, emissions, and automobile life-cycle environmental accounting. *Environmental Research Letters*, *5*(3), 034001.

Christaller, W. (1966). *Central places in southern Germany*. Prentice-Hall.

CityMobil2 Project. (n.d.). CityMobil2 Project. Retrieved February 15, 2016, from http://www.citymobil2.eu/en/About-CityMobil2/Overview/

Coyne, J. (2015, May 22). Here's your first look at Uber's test car. Retrieved February 15, 2016, from http://www.bizjournals.com/pittsburgh/blog/techflash/2015/05/exclusive-heres-your-first-look-at-ubers-self.html

DARPA. (n.d.). DARPA Urban Challenge. Retrieved February 24, 2016, from http://archive.darpa.mil/grandchallenge/

de Palma, A., Picard, N., & Waddell, P. (2007). Discrete choice models with capacity constraints: An empirical analysis of the housing market of the greater Paris region. *Journal of Urban Economics*, *62*(2), 204–230.

Douglas, K. W. (2015). *Truly Empty Vehicle Repositioning and Fleet Sizing: Optimal Management of an Autonomous Taxi System in New Jersey on a Typical Weekday.* Princeton University.

Dueker, K. J., Bair, B. O., & Levin, I. P. (1977). Ride-sharing: psychological factors. *Transportation Engineering Journal of the American Society of Civil Engineers*, *103*(6), 685–692.

Elmer, S. (2013). BMW targets 2020 for self-driving cars. *AutoGuide, February*, *26*.

Fagnant, D. J., & Kockelman, K. (2015a). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181.

Fagnant, D. J., & Kockelman, K. M. (2013). Preparing a Nation for Autonomous Vehicles Eno Center for Transportation. *Washington, DC*.

Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, *40*, 1–13.

Fagnant, D. J., & Kockelman, K. M. (2015b). Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. In *Transportation Research Board 94th Annual Meeting*.

Fagnant, D. J., Kockelman, K. M., & Bansal, P. (2015). Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market. *Transportation Research Record: Journal of the Transportation Research Board*, (2536), 98–106.

Fan, W., Machemehl, R., & Lownes, N. (2008). Carsharing: Dynamic decision-making problem for vehicle allocation. *Transportation Research Record: Journal of the Transportation Research Board*, (2063), 97–104.

Ford, H. J. (2012). *Shared Autonomous Taxis: Implementing an Efficient Alternative to Automobile Dependency*. Princeton University.

Geisberger, R., Luxen, D., Neubauer, S., Sanders, P., & Volker, L. (2009). Fast detour computation for ride sharing. *arXiv Preprint arXiv:0907.5269*.

Ghoseiri, K., Haghani, A. E., Hamedi, M., & Center, M.-A. U. T. (2011). *Real-time rideshare matching problem*. Mid-Atlantic Universities Transportation Center.

Google. (n.d.). Google Self-Driving Car Project. Retrieved February 24, 2016, from http://www.google.com/selfdrivingcar

Google Monthly Report. (2016, January). Google Self-Driving Car Project Monthly Report - January 2016.pdf. Retrieved February 15, 2016, from https://static.googleusercontent.com/media/www.google.com/en//selfdrivingcar/files/reports/report-0116.pdf

Guimaraes, P., Figueiredo, O., & Woodward, D. (2004). Industrial location modeling: extending the random utility framework. *Journal of Regional Science*, *44*(1), 1–20.

Guo, J. Y., & Bhat, C. R. (2007). Operationalizing the concept of neighborhood: Application to residential location choice analysis. *Journal of Transport Geography*, *15*(1), 31–45.

Habib, M., & Miller, E. (2009). Reference-dependent residential location choice model within a relocation context. *Transportation Research Record: Journal of the Transportation Research Board*, (2133), 92–99.

Hayes, B. (2011). Leave the Driving to it. *American Scientist*, *99*, 362–366.

IHS Automotive. (2014). Self-Driving Cars Moving into the Industry's Driver's Seat | IHS Online Newsroom. Retrieved February 15, 2016, from http://press.ihs.com/press-release/automotive/self-driving-cars-moving-industrys-drivers-seat

International Transport Forum. (2015). Urban Mobility System Upgrade: How shared self-driving cars could change city traffic.

Jofre-Monseny, J., & Solé-Ollé, A. (2010). Tax differentials in intraregional firm location: evidence from new manufacturing establishments in Spanish municipalities. *Regional Studies*, *44*(6), 663–677.

Johnson, D. (2013). Audi predicts self-driving cars by 2020. *Left Lane*.

Kessler, A. M. (2015). Elon Musk Says Self-Driving Tesla Cars Will Be in the US by Summer. *The New York Times. Http://Mobile. Nytimes. Com/2015/03/20/Business/Elon-Musk-Says-Selfdriving-Tesla-Cars-Will-Be-in-the-Us-by-Summer. Html*.

Kleiner, A., Nebel, B., & Ziparo, V. (2011). A mechanism for dynamic ride sharing based on parallel auctions.

Kornhauser, A. (2013). Uncongested mobility for all: New Jersey's area-wide aTaxi system. Princeton University. *Operations Research and Financial Engineering. Retrieved September*, *23*, 2013.

KPMG. (2015). Connected and Autonomous Vehicles - The UK Economic Opportunity. Retrieved from http://www.smmt.co.uk/wp-content/uploads/sites/2/CRT036586F-Connected-and-Autonomous-Vehicles-%E2%80%93-The-UK-Economic-Opportu...1.pdf

Lee, B. H., Waddell, P., Wang, L., & Pendyala, R. M. (2010). Reexamining the influence of work and nonwork accessibility on residential location choices with a microanalytic framework. *Environment and Planning A*, *42*(4), 913–930.

Levin, M. W., Li, T., Boyles, S. D., & Kockelman, K. M. (2016). A general framework for modeling shared autonomous vehicles. In *95th Annual Meeting of the Transportation Research Board*.

Losch, A. (1954). Economics of location.

Markoff, J. (2014). Google's next phase in driverless cars: No steering wheel or brake pedals. *New York Times*.

Marshall, A. (2009). *Principles of economics: unabridged eighth edition*. Cosimo, Inc.

McFadden, D. (1978). Modeling the choice of residential location. *Transportation Research Record*, (673).

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *The American Economic Review*, *57*(2), 197–210.

Pinjari, A. R., Bhat, C. R., & Hensher, D. A. (2009). Residential self-selection effects in an activity time-use behavior model. *Transportation Research Part B: Methodological*, *43*(7), 729–748.

Pinjari, A. R., Pendyala, R. M., Bhat, C. R., & Waddell, P. A. (2011). Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions. *Transportation*, *38*(6), 933–958.

Rigole, P.-J. (2014). Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm.

Shen, W., & Lopes, C. (2015). Managing Autonomous Mobility on Demand Systems for Better Passenger Experience. In *PRIMA 2015: Principles and Practice of Multi-Agent Systems* (pp. 20–35). Springer.

Shoup, D. C. (2005). *The high cost of free parking* (Vol. 7). Planners Press, American Planning Association Washington, DC, USA:

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., & Pavone, M. (2014). Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in Singapore. In *Road Vehicle Automation* (pp. 229–245). Springer.

Stanley, M. (2013). Autonomous cars: self-driving the new auto industry paradigm. *Blue Paper*.

The Economist. (2013). Look, no hands. Retrieved March 7, 2016, from http://www.economist.com/news/special-report/21576224-one-day-every-car-may-come-invisible-chauffeur-look-no-hands

von Thünen, J. H. (1826). Der isolierte Staat in Beziehung auf Nationalökonomie und Landwirtschaft. *Gustav Fischer, Stuttgart (Reprinted 1966)*.

Waddell, P., & Ulfarsson, G. F. (2003). Accessibility and agglomeration: discrete-choice models of employment location by industry sector. In *82nd annual meeting of the Transportation Research Board, Washington, DC* (Vol. 63).

Wang, H., Cheu, R., & Lee, D.-H. (2010). Dynamic relocating vehicle resources using a microscopic traffic simulation model for carsharing services. In *Computational*

Science and Optimization (CSO), 2010 Third International Joint Conference on (Vol. 1, pp. 108–111). IEEE.

White, J. (2013). Nissan expects to market self-driving cars by 2020. *Wall Street Journal*.

Zhang, W., & Guhathakurta, S. (2017). Parking spaces in the age of shared autonomous vehicles: How much parking will we need and where? In *Transportation Research Board 96th Annual Meeting*.

Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015a). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, *19*, 34–45.

Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015b). The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach. In *Transportation Research Board 94th Annual Meeting*.